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Anticipatory Vehicle Routing

Coordinating traffic using community generated traffic predictions

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Dissertation presented in partial fulfillment of the requirements for the degree of PhD in Engineering Science: Computer Science

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Nothing in life is to be feared, it is only to be understood. Now is the time to understand more, so that we may fear less.

– Marie Curie

Abstract

The number of vehicles on the road keeps rising every day. This increasing demand for mobility puts more and more stress on the supply side of traffic: the road infrastructure. When the available capacity of the road network can no longer meet the demand put on it by the road users, traffic jams occur and time is wasted.

Information and Communication Technology already plays an important role in route guidance. By enabling fast information exchange modern day technology allows advanced traveler information systems to better inform the road users. This additional information should help road users make informed decisions when choosing their routes.

Traffic systems, with the large number of vehicles and wide spread traffic network, pose a number of challenges. Providing all road users with uniquely tailored information regarding their travel plans is made difficult by the scale and dynamic nature of traffic.

Delegate multiagent systems offer a set of patterns that can facilitate the design of multiagent systems. The patterns help by encapsulating the complex interactions needed to build coordination and control applications capable of coordinating large scale systems such as traffic. Delegate multiagent systems have been applied succesfully in other problem domains such as manufacturing control and service composition.

Traffic systems, with their scale and dynamism offer some challenges delegate multiagent systems is unable to deal with. The scale of the traffic network is too large to explore using delegate multiagent systems. The uncertainty and dynamism of traffic makes the reservation based mechanism used by delegate multiagent too rigid. These characteristics of traffic make it necessary to adapt the patterns provided by delegate multiagent systems.

This thesis describes a feasibility study of delegate multiagent systems for traffic management. To test the applicability of delegate multiagent systems in traffic, AntTIS, an anticipatory traveler information system was developed.

The goal of AntTIS is to help road users make better decisions, decisions that lead to shorter travel times, but also decisions that can delay congestion buildups. AntTIS relies on intention based traffic predictions to guide its users. It collects information about the route its users intend to follow and uses that information to predict the traffic conditions those users will experience while following that route, or an alternative route.

To collect this intention information and to distribute the traffic predictions back to all relevant road users, the AntTIS system uses a technique called delegate multiagent systems. Delegate multiagent systems facilitate the design and development of a multiagent system by encapsulating certain interactions and removing the top agents from those responsibilities.

The traffic predictions generated by AntTIS are based on the information shared by its users. This information from the community of users is combined with artificial neural networks to predict the time it takes a user to traverse a certain link. The AntTIS system autonomously maintains both the community provided information and the artificial neural networks that help model the links in the traffic network.

AntTIS is evaluated using extensive traffic simulations. Scenarios of both urban and regional size are simulated to assess the quality of the routing advice given to the road users. The evaluation shows that AntTIS, can adapt to traffic patterns and can help road users find good routes, especially in conditions where the road users lack prior knowledge about what traffic conditions to expect. In case of unusual traffic patterns or disturbances in the traffic network, routes provided by AntTIS are better than the routes users would choose based on prior knowledge.

Samenvatting

Het aantal voertuigen op onze wegen blijft dagelijks toenemen. De alsmaar stijgende vraag naar transport en mobiliteit plaatst onze weginfrastructuur onder druk. Wanneer de capaciteit van het wegen netwerk onvoldoende wordt en de toestroom aan voertuigen niet meer kan verwerken leidt dit tot filevorming en tijdsverlies.

Informatie en communicatie technologie speelt vandaag reeds een belangrijke rol in het verkeer. Technologie laat toe bestuurders beter en sneller te informeren. Die bijkomende informatie helpt de bestuurders betere beslissingen te nemen wanneer het aankomt op het kiezen van een geschikte route naar hun bestemming.

Het dagelijkse verkeer is een erg groot en dynamisch systeem. Het grote aantal voertuigen verspreid over een uitgebreid netwerk van wegen maakt het verzamelen en verspreiden van informatie op maat van de reiziger een uitdaging. De verkeerssituatie veranderd continue en dat maakt dat accurate verkeersinformatie vaak niet op één plek beschikbaar is.

Delegate multiagent systemen bieden een aantal patronen die het ontwerp van multiagent systemen vereenvoudigen. Deze patronen schermen de complexe interacties, nodig om controle en coordinatie applicaties voor grote systemen als verkeer te maken, af van de rest van het systeem. Delegate multiagent systemen zijn eerder succesvol toegepast in domeinen als productie planning en service composition.

Verkeer biedt omwille van de grootte en dynamiek een aantal uitdagingen waarmee delegate multiagent systemen nog niet overweg kunnen. De grootte van het verkeersnetwerk is zodanig groot dat het niet verkend kan worden met delegate multiagent systemen. De dynamiek en onzekerheid aanwezig in verkeer maakt dat het op reservatie gebaseerde systeem gebruikt door delegate multiagent systemen te rigide is. Deze eigenschappen van verkeer zorgen dat het noodzakelijk is de patronen aangeboden door delegate multiagent systemen

aan te passen.

Deze thesis beschrijft een haalbaarheidsstudie voor het gebruik van delegate multiagent systemen in verkeer. Om de toepasbaarheid van delegate multiagent systemen te testen is AntTIS, een anticiperend systeem dat informatie verschaft aan bestuurders ontwikkeld.

Het doel van AntTIS is bestuurders betere beslissingen te laten maken. Beslissingen die leiden tot kortere reistijden. Beslissingen, ook, die filevorming kunnen vertragen. Hiervoor gebruikt AntTIS informatie van de gebruikers. Informatie over de route die de gebruikers van het systeem van plan zijn te volgen. Deze informatie wordt verzameld en gebruikt om de toekomstige verkeerssituatie te voorspellen. Die voorspellingen kunnen bestuurders raadplegen om zo te leren welke verkeerssituatie ze zullen tegenkomen op hun route, of op eventuele alternatieve routes.

De informatie wordt door AntTIS verzameld en verspreid met behulp van multiagent systemen. Deze multiagent systemen vergemakkelijken het ontwerp en de implementatie van multiagent systemen door bepaalde delen van de functionaliteit te isoleren en af te schermen van de rest van het systeem. Hierdoor worden de andere agenten in het multiagent systeem van bepaalde verantwoordelijkheden verlost.

De voorspellingen die AntTIS genereert zijn gebaseerd op informatie die het ontvangt van de bestuurders. Deze informatie wordt gecombineerd met artificiële neurale netwerken om zo de tijd nodig om een weg af te leggen in te schatten. Het AntTIS systeem zorgt zelf voor deze artificiële neurale netwerken en houdt de informatie van de gebruikers accuraat.

AntTIS wordt geëvalueerd op basis van een aantal simulaties. Deze simulaties beschrijven scenarios van verschillende groottes: zowel stedelijke als regionale verkeersnetwerken. De evaluaties tonen aan dat AntTIS gebruikers helpt goede routes te kiezen. Vooral in situaties waarin bestuurders niet langer kunnen vertrouwen op hun ervaring om het verkeer in te schatten kan AntTIS helpen. Bij ongewone verkeersstromen of incidenten in het verkeersnetwerk zijn de routes die AntTIS voorstelt beter dan diegene die de gebruikers zonder het systeem zouden kiezen.

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Het boekje dat je nu leest is het eindproduct van vele jaren onderzoek. Onderzoek dat enkel mogelijk was dankzij het vertrouwen en de steun van mijn promotor Tom Holvoet en co-promotor Wouter Joossen.

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– Rutger Claes

Abbreviations

ANN	artificial neural network.
AntTIS	Anticipatory Traffic Information System.
ATIS	advanced traveller information system.
CDF	Cummulative Density Function.
dMAS	delegate multiagent system.
ETA	estimated time of arrival.
ETD	estimated time of departure.
GPS	Global Positioning System.
ICT	Information and Communication Technology.
ITS	Intelligent Transportation System.
MAS	multiagent system.
MLP	multi-layer perceptron.
SSOT	Single Source of Truth.
TMC	Traffic Message Channel.

V2I	Vehicle to Infrastructure.
V2V	Vehicle to Vehicle.

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Chapter 1

Introduction

The number of vehicles on the road keeps rising every day. This increasing demand for mobility puts more and more stress on the supply side of traffic: the road infrastructure. When the available capacity of the road network can no longer cover the demand put on it by road users, traffic jams occur and time is wasted.

Fixing the balance between traffic demand and supply can be done in two ways: increasing the inherent capacity at the supply side, or managing the traffic demand. In managing the demand side there are two options: trying to alter the number of vehicles on the road or trying to change the way the vehicles use the traffic infrastructure to reach their destination. Managing the traffic demand involves providing road users with additional information, this is achieved through the use of advanced traveller information systems (ATISs). The additional information could cause users to change the timing of their trip, thus altering the number of vehicles on the road at a given time. Or, the information could be in the form of route guidance, causing the drivers to alter their route and thus changing how the traffic demand is spread across the available traffic infrastructure.

ICT has played an important role in route guidance. Recent advances in technology have only increased its importance. Initially the role of ICT in route guidance was restricted to computation and communication. Routing algorithms enable software packages to propose optimal routes to road users based on information about the traffic network. Route guidance moved from an off-line process where road users would calculate a route before their departure to en route guidance using on board devices equipped with Satellite Navigation positioning.

Communicating traffic information to road users allows them to make en route changes to their plans. Technologies such as TMC allow for such communication. Informing road users of the current traffic conditions enables them to avoid currently known congestion.

Today's state of the practice route guidance systems combine computation and communication to provide adaptive route guidance. The route guidance system not only proposes a route to the road user. It continuously monitors the available information about the road network and proposes alternatives to the initial advice if this is necessary.

The next step for ICT in traffic is enabling coordinated traffic guidance. Current route guidance systems mostly operate in an isolated fashion. They do not take into account the impact of the information they share with their users, nor do they take into account the information shared with them by their users.

Anticipatory route guidance relies on making short term traffic predictions. Predictions about future traffic conditions are always based on information currently available about both the traffic network and traffic conditions. Current state of the art traffic predictions combine historical and real-time information about traffic conditions to predict future traffic conditions.

The main research question handled in this thesis is:

> Can delegate multi-agent systems be used as the core mechanism of an ATIS for large-scale coordination of traffic? And if so, what adaptations are necessary for delegate multi-agent systems to work in traffic?

This thesis describes a feasibility study of delegate multiagent system (dMAS) for traffic management. DMAS has been applied to coordination and control problems in other problem domains. Applying the patterns of dMAS help in encapsulating the complex interactions required to coordinate numerous entities in a dynamic and distributed environment. The patterns complement a multiagent system (MAS) based decomposition.

The ability of dMAS to deal with dynamism and scale make it a good candidate to be applied in the traffic domain. This thesis studies the feasibility of such an application by implementing an ATIS based on the patterns of dMAS. The ATIS implemented for this purpose is an anticipatory vehicle guidance system called AntTIS.

The thesis describes how dMAS allows us to overcome certain challenges in building the route guidance system, it also describes aspects of dMAS that needed to be altered for it to be applicable to the domain of traffic coordination. As such, this thesis is a feasibility study of dMAS in a traffic context.

The combination of the large scale and dynamic nature of traffic pose previously unseen challenges for the dMAS. By taking advantage of domain knowledge and machine learning techniques, the modifications described in this thesis allow dMAS to be applied in the traffic domain.

The route guidance system presented in this thesis uses currently available information on the future plans of road users. The challenge in predicting the traffic conditions thus shifts to collecting, aggregating and analyzing the plans of the road users.

1.1 Context

If every road user would simply calculate the shortest route to his destination, traffic would be a disaster. However, road users learn from their everyday experiences and continuously adapt their routing behavior based on the lessons learned. This insight has been present for a long time and was noted by R. J. Smeed in 1967 [76]:

> The result of all choices that people make is that traffic adjusts itself to the available capacity and that there is an oscillation about an equilibrium speed.

By choices, Smeed meant more than just route choices. Choices in mode of transport and departure time also play a role in this phenomenon. The traffic assignment evolves towards what is known in game theory as a *Nash equilibrium*: a situation where a set of non-cooperative players has knowledge about the strategy of the other players and has nothing to gain by changing its own strategy [92].

Road users make decisions to optimize their own journey times. This uncooperative behavior leads to a user equilibrium. This equilibrium is described by Wardrop's first principle [97]:

> The journey times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route.

A user-optimized equilibrium is a traffic flow in which no road user can lower his transportation cost through unilateral action. This describes the behavior of everyday commuters, or in general, the behavior of any road user with sufficient knowledge of the traffic conditions he will encounter. If such a road user knew a route with a lower cost, he would take it.

A system-optimized equilibrium is a traffic flow where the route followed by all road users is based on the maximum utilization of the network resources and a minimum total system cost. In a system-optimized traffic flow, some road users could change to a faster route but are not allowed to do so because such a change would cause other road users to suffer consequences. If the total cost of the consequences caused by the change outweigh the benefit experienced by the user making the change, the change is not allowed under a system-optimized equilibrium.

While the user equilibrium is not a system optimum, it is still far better than a traffic flow resulting from road users' decisions without prior knowledge. As in the latter case they would not take into account the traffic conditions they are likely to encounter and the journey times that these traffic conditions lead to.

When facing a disturbed traffic network, a traffic network in which some incident or disturbance has altered either traffic demand or network capacity, even experienced road users have little knowledge on which to base their routing decisions. Examples of incidents or disturbances are traffic accidents, road works or holiday traffic patterns. At that point, route guidance systems informing road users of the traffic conditions become a necessity to ensure a smooth traffic flow. These disturbances lead to what is called non-recurrent congestion. It is precisely this non-recurrent congestion that potentially benefits the most from traveller information systems [45, 43].

1.2 Problem statement

Current ATISs work in an isolated fashion. When dispensing routing advice to road users, advice given to other users or information obtained from other users is not taken into consideration. Thus every road user is guided towards his destination individually.

Providing road users with short term traffic predictions will allow them to avoid congestion buildup. However, obtaining these short term predictions, sharing them with the road users and using the predictions to better coordinate the road users poses several challenges.

Obtaining all relevant information to formulate the short term traffic predictions and offering those predictions back to the vehicles that want to make use the information requires a lot of interactions between the different components in the AntTIS system. Applying the patterns provided by dMAS can help deal with these challenges. DMAS will encapsulate the complex interactions and in doing so, simplifies the design of the components responsible for these interactions.

The AntTIS system was built using a MAS based architecture. The patterns of dMAS are applied on the interactions between the different agents in this MAS. The dMAS patterns facilitate the design of the AntTIS system. The complex interactions necessary to provide vehicles with predictive route guidance in an environment as large-scale and dynamic as traffic is largely shielded from the agents.

The scale and dynamism of the traffic domain does pose a set of previously unseen challenges for the patterns in the dMAS approach. It is these problems that are tackled in this thesis. By applying dMAS to the traffic coordination problem we identify alternate ways of applying dMAS patterns to large scale and dynamic systems.

Alternatives to delegate multi-agent systems exist. Such other mechanisms that allow indirect communication between agents in multi-agent based traffic coordination systems such as Ant Based Control [84, 83, 82] and BeeJamA [99, 73, 74] focus more on storing information in the environment and less on managing the interactions between the individual agents directly. These techniques and how they differ from the approach taken in this thesis are discussed in Chapter 7.

This section formulates the key problems that need to be addressed in order to use short term traffic predictions to coordinate the route guidance of road users in large scale dynamic traffic scenarios.

1.2.1 Short Term Traffic Predictions

Coordination of traffic can be facilitated by using short term traffic predictions. By creating an anticipatory system, the coordination can anticipate undesired traffic conditions and guide the road users so as to avoid the undesired conditions.

However, making predictions about the time it will take for a vehicle to traverse a certain link in the traffic network is a challenging problem, even if the traffic predictions are only short term. Various parameters, including the link characteristics and the number of other vehicles, influence the link traversal time.

Obtaining all these parameter values and modelling how they influence the traversal time of a link is a key problem that needs solving in order to make short term traffic prediction feasible.

Key Problems

- Road users' intentions need to be collected and aggregated for them to serve as the basis of the short term traffic predictions.
- Not all road users will participate in the route guidance system. Road users not participating in the system will not share their intentions with the system.

Key Challenges

- Collecting the intentions from a vast number of road users.
- Managing the dynamic nature of the intentions.
- Dealing with the fact that not all road users will share their intentions.

1.2.2 Coordination of a large scale and highly dynamic system

Traffic is inherently a large scale system. Belgium has an estimated 559 cars per 1000 inhabitants and that number has risen in the past years [1]. Providing coordination in a system of this scale is very challenging. A vehicles' route choice affects the traffic conditions encountered by a large set of other vehicles. And even though the effect of a single route choice in itself is almost negligible, it is the result of all route choices that cumulates to the everyday structural traffic jams.

Handling the large scale of traffic is not the only challenge faced when coordinating road users. Dynamism is another challenge that contributes to the difficulties. Traffic conditions are subject to a great number of influences. Influences external to the traffic domain such as the weather, vacations or strikes have a big impact on traffic. But also internal disruptions such as accidents and road works can influence traffic conditions.

The presence of such dynamism means the coordination of road users is an ongoing process and that road users have to be guided throughout their journey based on the latest available information.

Short term traffic predictions can only be based on information available to the system at the point the prediction is made. Because of the dynamic nature of traffic, the short term predictions will also change over time.

Key Problems

1. **Scale** Delegate multiagent systems have been previously applied to facilitate coordination in domains that show a graph-like structure. The graph representation of the traffic network is an order of magnitude larger than the graphs present in problem domains dMAS was applied in previously. Not all exploration of the graph can be handled by dMAS.

   Not only the graph in which the coordination takes place is very large, the number of road users making use of the traffic infrastructure is also very large. These road users are geographically distributed across the entire traffic network. The short term traffic predictions offered by AntTIS require information from all of the participating vehicles.

2. **Dynamism** Traffic is a very dynamic system. Traffic conditions are constantly changing. The large number of road users involved together with outside influences such as weather and the possibility of accidents can rapidly alter traffic conditions. The reservation based system previously used by coordination and control systems based on dMAS is too rigid for a problem domain as flexible as the traffic domain.

Key Challenges

- Managing the information exchange between the large number of entities involved in the coordination is challenging.
- Exploration of a graph environment as large as the one in the traffic domain is unfeasible using the exploration strategy proposed by dMAS.
- Continuously adapting the coordination to the latest traffic conditions.

1.3 Contributions

The work described in this thesis takes delegate multiagent systems as a starting point and adapts it to work in the context of anticipatory vehicle routing.

The anticipatory vehicle routing is achieved by implementing an ATIS that offers proactive routing advice to road users. This ATIS is designed as a multiagent system.

Delegate multiagent systems have been used in various domains to facilitate coordination in coordination-and-control applications, applications in which a decentralized coordination system coordinates a physical system to achieve complex coordinated behavior. Delegate multiagent systems simplify the design and implementation of the agents that control such a physical system.

While delegate multiagent systems have been applied in other domains, using it in the context of route guidance in traffic required some modifications.

More background information on multiagent systems and delegate multiagent systems can be found in Section 2.3 and Section 2.4.

To address the challenges listed in the previous section, this thesis provides the following three contributions:

1. **Delegate multiagent systems based evaluation of routes in large-scale traffic networks**

   The AntTIS system uses delegate multiagent systems to evaluate a number of candidate routes for every vehicle. The AntTIS system first calculates a number of route candidates based on the static traffic network information and only then uses mobile agents to evaluate the quality of those routes.

   Exploring large graph structures using ACO has proven to be too difficult. ACO is a good search technique when facing large unknown graphs. It does not perform so well in graphs as large as urban or nation-wide traffic networks.

   The mobile agents in AntTIS therefore do not explore the graph representation of the traffic network. Previous applications of delegate multiagent systems used an ACO based exploration strategy to explore the graph in which they operate out of necessity given the dynamic nature of the graph structure. In traffic networks, the structure of the graph is not dynamic. Roads do not suddenly appear. It is the weight of the graph that can change rapidly in traffic networks. Evaluating a predefined set of routes yields reasonable results and is more robust and scalable.

2. **Short term traffic predictions using machine learning in dynamic traffic networks**

   In the AntTIS system, Infrastructure Agents provide Vehicle Agents with predictions. This is unlike other applications of delegate multiagent based coordination and control systems where the Infrastructure Agents would use a reservation based system to inform other agents of free slots.

   The characteristics of traffic and in particular its dynamic and uncertain nature make it unrealistic to use a rigid reservation based system to keep track of which vehicle will occupy which road section. A system coordinating traffic has to deal with the uncertainty caused by influences not under its control. Examples of such influences are cyclists, pedestrians, weather, incidents and - at least for now - human driver behaviour. The uncertainty introduced by these external influences make it impossible to enforce a reservation based approach. A vehicle that fails to vacate its slot due to a passing pedestrian cannot be expected to disappear and allow the reservation holder to take its place. Instead of the rigid reservation based system, a more flexible approach based on machine learning was used to translate the information provided by the Vehicle Agents into predictive information that the Vehicle Agents themselves could use in making better routing decisions.

The flexible machine learning approach relies on artificial neural networks to map information obtained from the vehicles combined based on a learning process driven by information captured from the traffic network. This flexible machine learning approach has a second benefit over the more rigid reservation based system. The artificial neural networks can take into account partial participation rates. Since the artificial neural networks do not require an explicit model of the underlying system, the un-participating vehicles do not need to be modelled. Instead, their influence is learned based on observations.

3. **Intention level information aggregation**

   The AntTIS system aggregates the intentions it receives from the vehicles into intention levels. These intention levels allow Infrastructure Agents to manage the flood of information they receive from Vehicle Agents. The intention levels replace the reservation based information storage found in most other delegate multiagent system based coordination and control applications.

   The intention levels combine the best of both worlds. They aggregate information provided by the vehicles in a way that resembles the use of pheromones in ACO. This enables us to use the aggregated information as input for the prediction process. On the other hand, just as in most other delegate multiagent systems based coordination and control applications, the ownership of an intention can still be traced back to an individual vehicle. That information is not discarded in the aggregation process and can be used to maintain the freshness and correctness of each individual intention through a process resembling the evaporation process also used in ACO based approaches.

1.4 Overview of this thesis

We conclude this chapter with an overview of the thesis.

Chapter 2 provides an overview of the domains in which this thesis is situated: Traffic, ATIS, Anticipatory Systems, MASs and dMASs.

Chapter 3 introduces the anticipatory route guidance system, AntTIS. The chapter focusses on the multiagent structure used to model the system, and the swarm based intention propagation and route evaluation approach.

Chapter 4 focusses on the short term predictions used in the anticipatory route guidance system. The chapter describes the artificial neural network based approach used to calculate the predictions based on the intention propagation by the road users.

Chapter 5 describes how the anticipatory route guidance system described in Chapter 3 will be evaluated. Focus of the description will be the experiment setup, possible metrics to measure the effectiveness of a route guidance system, and the base line to compare our anticipatory route guidance system with.

Chapter 6 presents the results obtained through the simulation of the scenarios and methodology described in Chapter 5.

Chapter 7 positions the contributions in this thesis with respect to related work. The chapter focusses on other ATISs that share characteristics with AntTIS.

Chapter 8 draws conclusions, restates the main contributions, and discusses the possibilities for future work.

Chapter 2

Background

The goal of the AntTIS route guidance system is demand side management of traffic. By assisting road users in making route choices, the system tries to shape traffic demand according to the traffic network capacity. Some understanding of the dynamics of traffic is necessary to evaluate how well AntTIS succeeds in reaching this goal.

Systems that guide users in making route choices are referred to as advanced traveller information systems (ATISs). Such systems collect relevant traffic information, analyze the information and present it to the road user in a format that helps the road user make informed route choices.

The way AntTIS tries to reach this goal involves short term traffic predictions. As such, the AntTIS system is an anticipatory system: it guides road users based on anticipated traffic conditions instead of simply the real-time observed traffic conditions.

AntTIS is modelled as a multiagent system (MAS). MASs are often used to build ATISs [10]. Traffic is inherently a geographically distributed large scale coordination problem. Such coordination problems are a good fit for MAS.

In order to reduce the complexity of coordinating a system as large scale and as dynamic as traffic, AntTIS employs a technique called delegate multiagent system (dMAS). Using a dMAS is a way to efficiently handle the interaction between a large number of software agents.

Overview This chapter discusses four topics: ATISs, anticipatory systems, MASs, and dMASs. First Section 2.1 discusses ATISs and how they can assist road users. Section 2.2 discusses anticipatory systems. Section 2.3 discusses MAS. And finally, Section 2.4 dMAS.

2.1 Advanced Traveler Information Systems

2.1.1 Traffic demand and supply

The number of vehicles on the roads every day keeps rising. This increasing demand for mobility puts more and more stress on the supply side of traffic: the road infrastructure. When the available capacity of the road network can no longer cover the demand put on it by road users, traffic jams occur and time is wasted.

Fixing the balance between traffic demand and supply can be done in two ways: increasing the inherent capacity at the supply side, or managing the traffic demand. When demand on a traffic network link surpasses its capacity, the throughput of that link will start to diminish [96, 40]. This is known as the *fundamental diagram* (Fig. 2.1). In order to optimally use a link, the number of vehicles utilizing that link should be below its capacity. Growing the capacity of the road network achieves this. By increasing the capacity, it is less likely that it will become saturated, and that its throughput will diminish. However, the growth of road networks has its limits, its capacity can not be increased endlessly. Besides, studies show that traffic demand will quickly catch up with increased traffic capacity because of latent demand and induced traffic [41]. So as the expansion of traffic networks is reaching its boundaries, the second option of balancing supply and demand - managing the traffic demand - becomes the more sustainable option.

2.1.2 An Overview of Advanced Traveler Information Systems

Drivers combine multiple sources of information when making decisions concerning their routes. They combine information from conventional sources such as personal experience, word of mouth and media messages. Drivers only relying on these information sources have incomplete information and this will lead to suboptimal routing decisions [12].

ATISs can offer additional information to drivers. The ATIS can provide this information in a number of ways, including traffic information broadcasting systems, pre-trip electronic route planning, on-board navigation systems; and electronic route guidance systems.

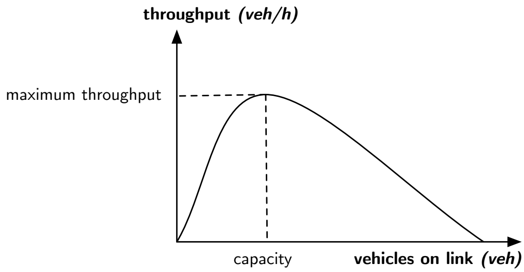


Figure 2.1: The relationship between the throughput of a link and the number of vehicles traversing that link shown in the fundamental diagram of traffic. Oversaturation of a link results in a reduced throughput.

An ATIS can play various roles in helping drivers reach better routing decisions. The ATIS can offer additional information about the traffic network, thus helping the road user decide on which route to choose. This is typically done through traffic information broadcasting, for example through mobile internet connections, traffic message channel (TMC) [36]), or through electronic route guidance systems. Other ATIS directly inform the driver of the most efficient route between his current position and his destination. This can be done before the trip starts or it can be an ongoing route guidance on-board.

ATISs can be categorized as either *static* or *dynamic* systems [72]. In static systems, the routing advice offered to the driver will not change over time, while in dynamic systems the routing advice will change depending on changing traffic conditions. ATISs offering pre-trip advice are most likely static systems, while systems that operate on-board have the possibility of being dynamic systems.

Route guidance offered by static ATISs is typically based on a shortest path algorithm. A path is calculated before the trip starts based on information available at that time.

While dynamic ATISs are typically more robust than static ATIS systems, they also have much more demanding requirements. The ability of dynamic systems to adapt the advice based on changes allow a dynamic system to handle unforseen changes. It can also lead to unstable behavior. In order for them to adapt their advice to updates in the traffic conditions they need communication abilities. With the advantages offered by dynamic systems over static systems and the recent day advances and adoption of wireless systems, almost all ATISs are developing dynamic capabilities.

One of the most used mechanisms to provide dynamic route guidance is by incorporating information broadcasted through the TMC system. This system is very efficient because it broadcasts real-time traffic information to a very large number of drivers. On-board navigation systems can use the information they receive to dynamically update the routing advice offered to drivers. TMC has certain technical limitations and the information it can carry is limited in two ways: (1) information about the kind of incident is restricted to a set of types; and (2) the location of the incident can only be described at a coarse grained level. Many satellite navigation systems use TMC nevertheless because it is a relatively simple mechanism to offer some real-time traffic information to the road user.

Information offered to the driver may fall into one of three categories [12, 93]: (1) historical information, (2) real-time information; or (3) predictive information. Predictive information can futher be split into behavioral consistent prediction and prediction based on extrapolation of the current traffic network state [68]. Current state of the art ATISs will combine information from all three categories to provide the driver with the most complete and accurate view on the current traffic conditions.

From the three categories listed above, the predictive information is the most valuable for the driver. Predictive information will describe the traffic conditions the driver will encounter, and thus should play an important role in evaluating the quality of a route. Based on the type of date used ATISs can be categorized as either *reactive* or *predictive* [72].

Reactive ATISs base their routing advice solely on the current traffic conditions (possibly augmented with historical information about the traffic conditions under similar circumstances). Recent advances in wireless communication technology and road sensors together with the increasing prevalence of smart phones enables ATIS systems to gather enormous amounts of detailed and accurate real-time information. Systems such as Google Navigation [104] and Waze [2] use information (Floating Car Data or user reported information) obtained from their drivers to estimate current traffic conditions.

Both reactive and predictive route guidance systems are of great use to the drivers. Reactive route guidance systems are less complex and can be implemented at a lower cost, however a predictive system will provide greater immunity to building congestion [72]. When predicting a traffic buildup on a traffic network link, a predictive ATIS can steer away drivers that had previously committed to using that traffic network link. This reduces the traffic buildup and can avoid congestion from forming.

A third axis which can be used to categorize ATISs is the *centralized* versus *decentralized* axis. Here the categorization is not that straightforward.

Often some components of an ATIS system are centralized while others are decentralized. Current state of the practice systems such as the route guidance systems offered by online services such Google, Apple and Waze; and satellite navigation route guidance such as TomTom and Garmin all have at least one centralized component.

In literature, the distinction between centralized and decentralized is typically not made based on the systems' architecture, but rather on where the routing decision is made. For example, the ATIS described by Wunderlich et al. [109] is labeled as decentralized by the authors because the route for every driver is calculated on-board of the drivers vehicle. The predictive information on which this calculation is based is however calculated by a central service. Similar decompositions can be found in many other ATIS systems.

Much of the research into truly decentralized ATISs focusses on V2V or V2I communication as it was an essential precondition to decentralization. However, with modern day prevalence of smart phones and the steady improvement of mobile internet V2V and V2I are no longer essential to truly decentralized ATISs.

Some state of the art ATISs described in literature take communication - be it through a combination of V2V and V2I or over the Internet - as a given and focus instead on how traffic state estimation and prediction can be done in a decentralized manner [108, 38, 83]. These ATISs have no central components and take full advantage of the benefits offered by decentralized systems.

The information provided to the road users by an ATIS does not necessarily lead to an improvement of the traffic conditions and an increase in traffic throughput. If the information provided to the road users is accurate and no external incentives are offered, an ATIS will steer road users towards a user equilibrium as described in Section 1.1.

Providing users with additional information can have other consequences. An ATIS that provides road users with information based on observations it makes in the traffic network forms a feedback loop. Such a feedback loop can potentially lead to instability and oscillation as shown in [94, 46, 58].

In ATIS applications where users are not totally myopic and are hesitant to switch to an alternative route unless that alternative is significantly better, these instabilities and oscillations are not problematic or are not observed [57, 46, 58, 95].

2.2 Anticipatory Systems

In his book “Anticipatory Systems” [70], Rosen defines an Anticipatory System as:

> A system containing a predictive model of itself and/or of its environment, which allows it to state at an instant in accord with the model’s predictions pertaining to a later instant.

Contrary to a reactive system which only takes into account past or present information, an anticipatory system will make choices based on information about its future state. Anticipatory behavior is one in which a change of state in the present occurs as a function of some predicted future state

An anticipatory system consists of three main components: the object system, the effectors and a model of the object system (Figure 2.2). The object system is the system of interest, the system whose state we want to manage. The effectors are a means of influencing the object system based on the state of the model.

The main requirement for an anticipatory system is a predictive model, a model that in its present state provides information about future states of the object system. The model receives the same environmental inputs as the system under its control. However, compared to the object system, the predictive model reacts faster to these influences.

The anticipatory system will influence the object system based on the state of the prediction model. If the predictive model moves towards an undesired state, the effectors will influence the system in such a way as to avoid the undesired state.

When coupled with an ATIS capable of predicting it future traffic conditions, traffic systems can be considered anticipatory systems. The ATIS maintains a model of the traffic network and the traffic conditions present on the network. When the ATIS is able to predict future traffic conditions, it can advice road users to take a different action and thus changes the inputs to the system. Using advice to road users as effector, the ATIS can steer the traffic system away from unwanted states, e.g. states in which congestion builds up in the traffic network.

2.3 Multiagent Systems

MASs are software systems composed of multiple autonomous software agents. The overall functionality of the software system is achieved through the interactions between the individual agents.

An intelligent, autonomous agent can be defined as

> An agent is a computer system that is situated in some environment and that is capable of autonomous action in this environment in order to meet its design objectives.

This definition was proposed by Wooldridge [107]

According to this definition an agent is situated in an environment. The actions the agent takes are typically meant to influence this environment. It is important to note however, that the agent has no complete control over its environment. The outcome of its actions are not guaranteed. They might not have the desired effect. It is essential for the agent to continuously monitor its environment and to adapt its behavior to the ever changing state of its environment in order to achieve its design objectives.

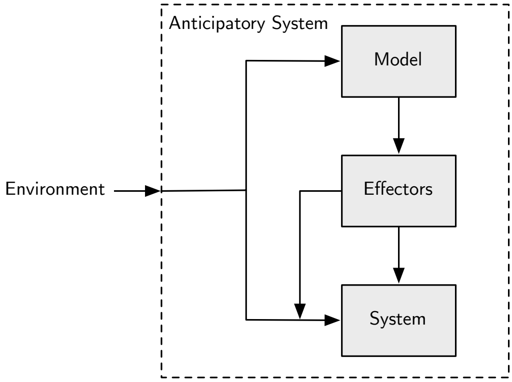


Figure 2.2: Both the model and the system are influenced by the environment. The model has a set of effectors that can influence the system directly or that can change the environmental inputs to the system. These influences will change the dynamical properties of the system. The combination of Model, the Effectors and the System forms the Anticipatory System. Figure based on [70].

An attribute often ascribed to agents or intelligent agents in a MAS is pro-activeness. An agent is not limited to just reacting to changes in the system. It can also take initiative and pro-actively take actions to achieve a desired system state. This pro-active behavior is what distinguishes MASs from other purely reactive systems such as actor based systems and object-oriented based systems. While these systems share some of the characteristics of a MAS, the entities (actors or objects) are not considered proactive.

By definition, MASs are decentralized. Software systems designed using a multiagent based architecture will not have a monolithic structure. Rather, the software will be composed out of a number of agents that all interact with each other.

The fact that MAS are by definition decentralized does not imply that all MASs are also distributed. A multiagent based system can be deployed on a single physical computation device, it can even be running in the same runtime environment.

The design principles behind a MAS do make it easier to distribute software with a MAS architecture. These benefits are not unique to MASs. Other architectural patterns such as actor based systems have similar benefits. The assumptions made while designing a system using a multiagent architecture, such as loose coupling between agents, asynchronous interactions between agents; and encapsulation of agent state, allow most MASs to be deployed in a decentralized environment.

Because of these characteristics MASs are a good fit for, and are often used in applications where information and interactions are geographically distributed.

A MAS is a system composed of individual interacting entities. As such, it represents a different way to compose the overall software system compared to a component based composition. Note that this does not imply that the agents defined in the MAS themselves cannot be composed out of components. Composition in a MAS occurs through the interaction of the agents. Where each agent is an autonomous software system in its own right and can initiate interactions pro actively.

2.3.1 Architectural Perspective on Multiagent Systems

In our research we consider MASs as a type of software architecture suited for large-scale, distributed, and decentralized software systems. As such, we follow the perspective proposed by Weyns in [102]:

> A multiagent system provides the software to solve a problem by structuring the system into a number of interacting autonomous entities embedded in an environment in order to achieve the functional and quality requirements of the system.

Designing a system based on a multiagent architecture offers some benefits. By decomposing a system based on agents and their interactions, certain non-functional requirements such as adaptability, scalability and robustness can be achieved.

The loose coupling between agents, the encapsulation of agent state and the explicit modelling of uncertainty when influencing the environment are some of the characteristics of a MAS design that lead to scalable and robust software systems.

These characteristics also pose challenges for the designers of the agents themselves. When designing an intelligent agent, one cannot assume the actions of the agent will take effect, all communication with other entities should be asynchronous and the agent decisions should be based solely on the knowledge possessed by that agent.

The non-functional requirements of the overall system may be fulfilled by decomposing it into individual agents and their interactions, but this shifts a lot of the complexity to the design of the individual agents. The decomposition does, however, break the challenges up so that they can be tackled one agent at a time.

In dealing with the challenges of designing individual agents and handling all the different responsibilities of an agent, patterns such as the ones described in Section 2.4 can be used to further reduce the complexity of the agent design.

2.3.2 Coordination in Multiagent Systems

The overall behavior of a MAS is determined by the outcome of the interactions between all individual agents and their environment. The interaction of the individual agents is likely to be influenced by the interactions between the agents. If there is no interaction between the agents, the MAS is little more than a collection of agents.

MASs composed of intelligent agents that are able to communicate and interact with each other are able to tackle more complex problems. This ability is sometimes referred to as the *social ability* of agents [100].

Most MASs are composed of cooperative agents. The agents all have a common objective or environment state they want to achieve. The actions of one of the cooperative agent might have an influence on the outcome of the actions of other agents. In deciding what actions to take, an agent should also consider the past, present and future actions of all other agents.

Precisely defining coordination is very hard. Coordination is said to be achieved when the “planned actions of all agents dovetail well”, when the “decisions of the agents jointly contribute to improving the collective state” or when the actions of an agent “establishes conditions for another agent that allow it to achieve desired shared goals” [100].

Coordination between agents can either be communicative or non-communicative [31]. In communicative MASs the agents deliberately send information to each other in order to coordinate their actions. In non-communicative MASs the agents coordinate their actions through observations of the environment. Examples of the latter are often found in nature. Many predators such as lions and wolfs hunt in a coordinated manner, deciding on their actions by observing the actions of their fellow hunters and the prey.

Many social insects go one step further and use the environment to communicate with each other and coordinate their actions [42, 32]. This form of indirect communication is called stigmergy. The use of stigmergy allows the insects to deliberately exchange information without having to explicitly communicate with one another. The main benefit of this approach is its scalability. A single insect can, through a slight alteration of the environment, communicate certain information with all insects able to perceive that alteration.

Communication through stigmergy is also possible in MASs and can be used to coordinate the actions of cooperative agents in a MAS.

Regardless of the means of communication the actions of individual cooperative agents in a MAS can be aligned either by taking into account coordination prior to planning or by coordinating the plans of individual agents after the plans have been formed.

An example of the prior is coordination through social laws and conventions. By imposing restrictions on the actions an agent can take, unwanted environment states can be avoided. An example of such a social law is driving on the right side of the road. This law will prevent collisions (the unwanted system state) as long as drivers take the restrictions into account prior to deciding on their actions.

Imposing certain interaction patterns is another form of coordination prior to planning. A consensus on which agent takes which action can be achieved by dictating how agents should interact with each other. An example of such interaction patterns are protocols like the Contract Net Protocol [77] and auctions.

Taking coordination into account prior to planning agent actions often leads to simple and elegant coordination mechanisms. It decouples the agents' local problems and allows them to plan independently. There are however also some downsides. Imposing restrictions on the actions an agent can undertake and the roles it can play can be restrictive and can lead to inefficiencies.

When coordination is taken into account after all agents have formed their plans, the coordination generally becomes more complex. All agents' plans have to be analyzed and possible conflicts should be identified. All such conflicts have to be resolved by adding additional constraints to the individual planning processes of the agents.

Such complex alignment of plans can only be achieved if the agents operate largely independent of each other, if their actions have little interdependencies and when these interdependencies are local to a small number of individual agents.

2.4 Delegate Multiagent Systems

The term *dMAS* has been used to describe different concepts. Initially it referred to a coordination mechanism that can be used to coordinate so called coordination-and-control applications, applications in which a decentralized coordination system coordinates a physical system to achieve complex coordinated behavior [48, 50]. The coordination mechanism models the physical system as a MAS consisting of two types of agents: *TaskAgents* and *ResourceAgents*.

The coordination mechanism relies on complex interactions between these two groups of agents. TaskAgents represent tasks that need to be accomplished. ResourceAgent represent various (physical) resources needed to accomplish these tasks. The end result of the coordination mechanism is not just a resource allocation but is a set of coordinated plans for every task describing which resource is to be used at what time. These plans are constructed and maintained throughout the coordination process.

To achieve this coordination, every TaskAgent interacts with a number of ResourceAgents. Because of the possibly large number of TaskAgents and ResourceAgents, the interactions can be become very complex. To handle the complexity, the complex interactions are encapsulated. A TaskAgent will *delegate* the interactions with all relevant ResourceAgents to a number of separate MASs. These MASs are also referred to as *dMASs*.

Encapsulating complex interactions by delegating them to a separate MAS is described as a pattern or a coordination pattern [49, 50]. The patterns rely on the concept of a *smart message*. Smart messages are self-contained entities that retain information about their sender and autonomously moves through a virtual environment. Often coordination mechanisms use not one smart message, rather they use a constant stream of smart messages. This stream of smart messages is managed. The rate at which they are sent and the path they need to traverse is determined. Such a managed conglomerate of smart messages is referred to as a dMAS, as the smart messages have agent-like characteristics.

2.4.1 Patterns of Delegate Multiagent Systems

In this thesis we use the term *dMAS* to refer to the pattern, not the coordination mechanism.

A dMAS facilitates the interaction between a single agent and a group of agents. When using a dMAS, there are several roles for various agents:

initiator The agent that initiates the interaction will instantiate the dMAS.

receiver The agents on the path of the smart message. These are the agents the smart message interacts with.

message The smart messages used in the dMAS have agent-like characteristics as they autonomously move through the environment and interact with the receiver agents.

The dMAS assumes that all receiver agents are arranged in a graph structure (Figure 2.3). In this graph, the receiver agents are the nodes. Smart messages are able to move through this graph and hop from receiver agent to receiver agent. DMASs are useful in situations where the coordination is heavily influenced by the structure of this graph.

One way in which the graph can influence the coordination is by structuring the group of receiver agents an initiator agent wants to interact with. The initiator agent, for example, might want to interact with all receiver agents on a path throughout the graph (Figure 2.4).

The smart message is sent out to an initial receiver by the initiator. It interacts with that receiver and moves on to the next receiver. The next receiver can either be decided on the go or be predefined.

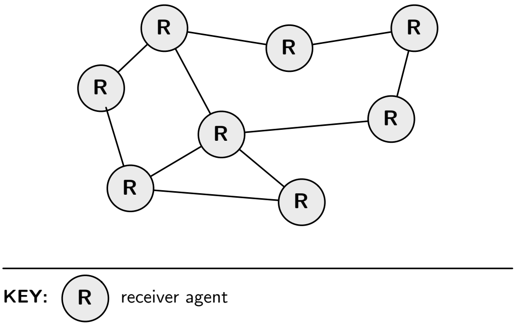


Figure 2.3: The dMAS assumes a graph structure connecting the receiver agents.

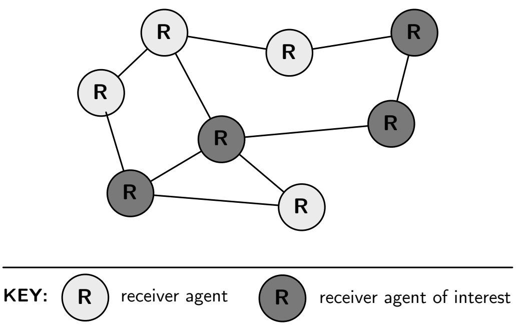


Figure 2.4: The graph structure containing the receiver agents should play a role in the coordination mechanism. Receiver agents of interest to an initiator agent could for example always form a path through the graph structure.

2.4.2 Use of Delegate Multiagent Systems patterns in coordination mechanisms

Initially dMASs was a term describing a concrete coordination mechanism. While in this thesis, the term dMAS is used to label a coordination pattern, the roles this pattern plays in the original coordination mechanism often recurs. This section describes these roles: exploration of the environment and disseminating intentions.

Delegation of exploration

Locality of knowledge and encapsulation of agent state are two principles in MAS design. A consequence of these principles is that every agent in a MAS is responsible for its own information retrieval. Either by making sure it is informed of all relevant information by other agents or by exploring the environment in which the agent is situated.

This exploration of the environment in which the agent is situated is not trivial, especially in large environments where information is distributed geographically. As mentioned in the previous sections, a dMAS can be used to interact in an efficient manner with a large number of other entities if they are structured in a graph.

By encapsulating knowledge about the environment in ResourceAgents and structuring these ResourceAgents in a graph, they become accessible for a dMAS which can then aggregate certain information from the environment.

Delegation of intention propagation

Coordination in a MAS often requires some sort of information exchange. To efficiently manage the complexity of coordinating the actions of large numbers of agents, the interactions between the actions should be localized and the action of one agent should only influence a small number of other agents.

Spreading the information necessary to coordinate the actions becomes increasingly complex as the number of actions and agents grows. Indirect communication mechanisms such as stigmergy help agents deal with this complexity. By placing relevant information about the agents planned actions - its *intentions* - in the environment, the agent can inform other agents of its future actions thus allowing other agent to coordinate their actions with its own.

This act of intention propagation can also be delegated to a separate MAS as described in the previous sections.

2.4.3 Delegate multiagent based coordination mechanisms

The dMAS based coordination mechanism described in Section 2.4.2 has been applied in a variety of domains. All these coordination problems can be characterised as coordination-and-control problems. Coordination problems in which a large number of entities need to be controlled to achieve an overall objective.

One of the first control-and-coordination problem in which dMAS based coordination was applied is manufacturing control [56, 55, 48, 87, 90]. In these applications, dMASs based coordination mechanisms are used to coordinate the planning at manufacturing plants.

DMASs based coordination is also applied in service composition problems. These problems deal with the allocation and composition of services in cloud environments. While the entities in this problem domain are not physical, they still exhibit the same characteristics: they are (geographically) distributed and connected in a graph like environment [37, 27].

A coordination mechanism that closely resembles dMASs is *Polyagents* [66]. Polyagents are avatars that impersonate the agent they represent and explore the environment on behalf of the agent they impersonate. A Polyagent simulates a possible path the impersonated agent could follow. It simulates the interactions and observations the impersonated agent would make if it would follow the same path as the Polyagent. Together, all the Polyagents representing one agent explore all possible futures of that agent. As such, Polyagents are used less as a coordination mechanism and more as a technique to offer decision support [65, 67].

Chapter 3

AntTIS: An Anticipatory Traffic Information System

The goal of advanced traveller information systems (ATISs) is to guide road users in making better routing decisions. They guide road users by providing them with relevant information about the different possible routes. Road users then choose the route that is most suited to their needs, evaluating the different routes based on information provided by the ATIS.

We aim to assess the feasibility of using the ideas and principles of delegate multiagent system (dMAS) as the basis for an ATIS system. The resulting ATIS is AntTIS, the system described in this thesis. Its goal is to collect information from both road users and the road network and present this information to the road users it guides in a way that helps the road user make good routing choices. By influencing the road users' decision process, the AntTIS system can coordinate traffic. By taking into account future traffic conditions, the AntTIS system can predict congestion buildups and, if an alternative route is available, the road user is guided away from the congestion. This can delay the congestion buildup. If the alternative is slower, or is also becoming saturated, the road users will again be guided towards the shortest path. Even if that causes congestion.

Collecting information, analyzing it, and using it to guide road users is challenging due to some of the characteristics of the environment in which the system operates: road traffic. Road traffic is a challenging problem domain due to several of its characteristics such as its large scale, its distributed nature, and dynamism.

Coordinating traffic involves coordinating a large number of individual road users that are geographically spread across the entire traffic network. The AntTIS route guidance system interacts with road users in two distinct ways: it collects information about the intentions of these users and it presents information about possible routes to these users. Both of these interactions are affected by the large number of road users and the fact that they are geographically distributed.

The dynamism in traffic networks also affects the coordination provided by the AntTIS system. Dynamism affects the coordination process in two ways. Firstly, because of changing traffic conditions, coordinating the road users becomes an ongoing concern. And secondly, the information stored by the AntTIS system has to be kept up to date.

Overview This chapter describes the main concepts behind the AntTIS route guidance system. Section 3.1 describes the overall architecture of the system. Section 3.2 and 3.3 discusses how the AntTIS system uses swarm based techniques to facilitate the interaction between the key components.

3.1 AntTIS architecture

The multiagent system (MAS) that forms the AntTIS consists of two main agent types namely the *Vehicle Agent* and the *Infrastructure Agent*. Vehicle Agents represent the road users side of the AntTIS system while Infrastructure Agents represent the traffic infrastructure on which the vehicles travel. Both of these agent types are described in more detail in the following sections.

The interaction between the two agent types is such that the Vehicle Agent provides Infrastructure Agents with information about what traffic infrastructure it will use and when it will arrive at the different links in the traffic network. The Infrastructure Agents provide the Vehicle Agents with predictions of the traffic conditions, allowing the Vehicle Agents to determine the most suitable route taking into account these predictions. These interactions are depicted in Figure 3.1.

The information provided by the Vehicle Agents to the Infrastructure Agents is referred to as the Vehicle Agents' intention. An intention consists of the route a Vehicle Agent intends to follow and the estimated arrival and departure times for each road on that route. Vehicle Agents share their intention with the Infrastructure Agents involved in that intention. Infrastructure Agents can aggregate the information shared with them and calculate the number of

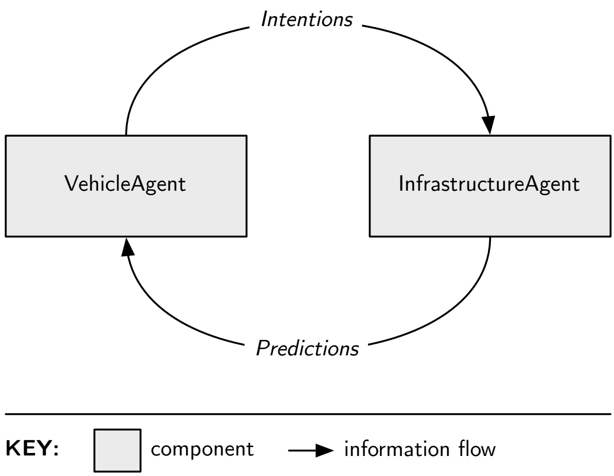


Figure 3.1: The two agent types interact to generate and maintain the traffic predictions and to make these predictions known to interested Vehicle Agents. The Vehicle Agents share their intentions with the Infrastructure Agents while the Infrastructure Agents share their intentions with the Vehicle Agents.

vehicles intending to traverse them at any given time. This vehicle count is referred to as the intention level at a given time for a given link in the road network.

The aggregation of the intention level data by the Infrastructure Agents ensures that information on the future traffic on a link is maintained by one agent. The Intention Agent is the Single Source of Truth (SSOT) for that information. For the overall quality of a route no such SSOT exists. All individual Vehicle Agents will have slightly different information about the overal quality of a route, dependent on the time they last updated their information on that route.

These interactions occur through two interfaces offered by the Infrastructure Agent, the *Traversal Time Prediction* interface allowing the Vehicle Agent to obtain link traversal time predictions and the *Intention Notification* interface allowing the Vehicle Agent to inform the Infrastructure Agent of its intention (Figure 3.2).

All agents, both the Vehicle Agents and the Infrastructure Agents operate in a virtual environment allowing them to communicate and interact with each other. The structure of this virtual environment resembles that of the road infrastructure the Infrastructure Agents represent. Both agents are *situated*

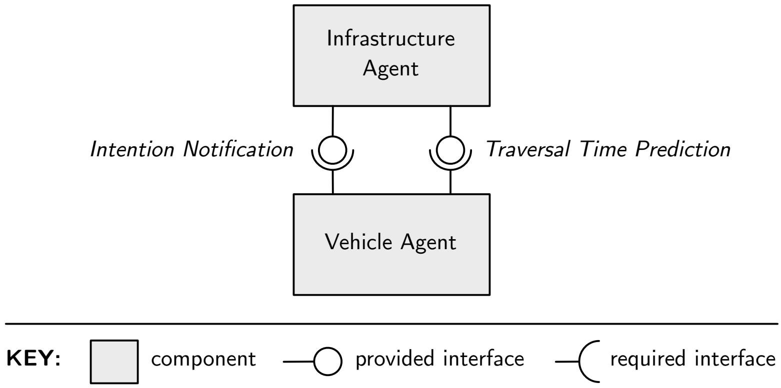


Figure 3.2: The MAS consists of two types of agents: Vehicle Agents and Infrastructure Agents. The Infrastructure Agent offers two interfaces to the Vehicle Agent: an *Traversal Time Prediction* interface allowing the Vehicle Agent to obtain link traversal time predictions for the link represented by the Infrastructure Agent and an *Intention Notification* interface allowing the Vehicle Agent to inform the Infrastructure Agent of its intention.

agents, they are situated somewhere in the virtual environment based on the location of the entity they represent in the real world.

In the virtual environment, Infrastructure Agents are connected in a graph structure. The structure of this graph corresponds to the structure of the road infrastructure. If two links are connected through an intersection in the real world, they are connected in the graph structure of the virtual environment. Figure 3.3 shows how the real world, the virtual environment and the Infrastructure Agents relate to each other.

Vehicle Agents are also situated in the virtual environment. Their location in the virtual environment is based on the link the road user they represent is currently traversing.

Key Challenges As the coordination mechanism relies heavily on the exchange of information between the Vehicle Agents and the Infrastructure Agents, managing the interactions dealing with the information exchange is crucial. Given the scale of the coordination mechanism, interactions between all entities should be avoided. This leads to the following two challenges:

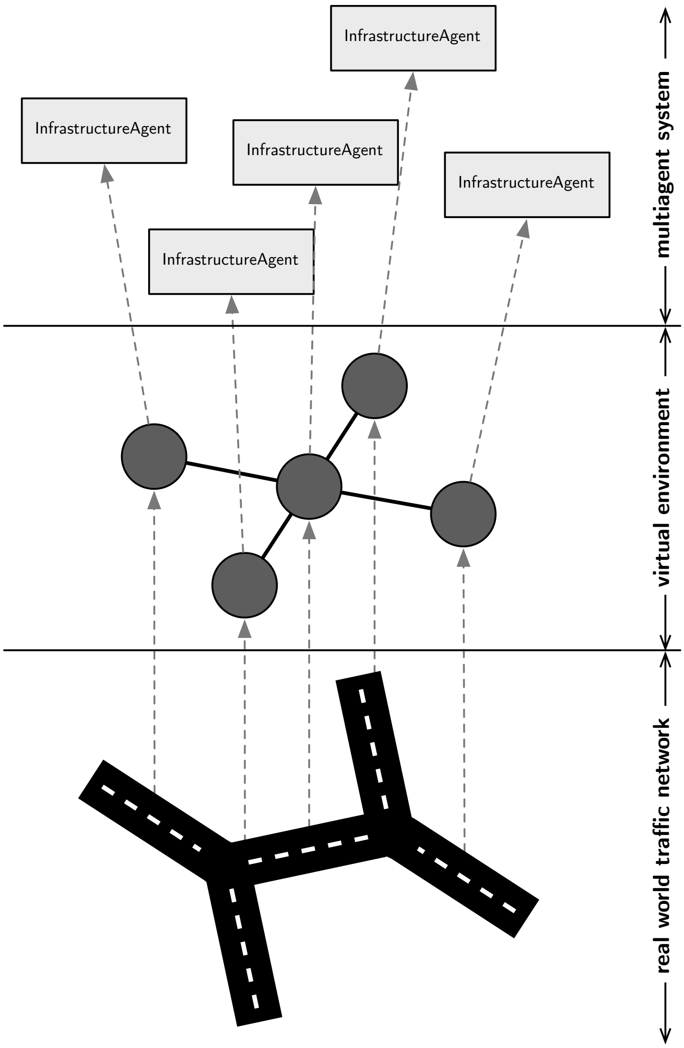


Figure 3.3: Infrastructure Agents are situated in the virtual environment. The virtual environment defines a graph structure whose structure is based on the layout of the real world traffic network. The layout of the virtual environment helps the MAS coordination by offering indirect information about the structure of the real world.

- **Limiting the interactions between the Vehicle Agents and the Infrastructure Agents** The Infrastructure Agents depend on information from the Vehicle Agents to achieve their goals. However, Vehicle Agents, should only inform relevant Infrastructure Agents of their intentions.
- **Limiting the interactions between the Infrastructure Agents and the Vehicle Agents** Vehicle Agents make their own routing decisions. In order to do so, they need the link traversal time forecasts generated by the Infrastructure Agents. However, these forecasts should only be generated and shared with Vehicle Agents that take an interest in the link the Infrastructure Agent represents.

The AntTIS system is designed as a decentralized MAS. The benefits of MAS architectures are already discussed in Section 2.3. Decentralized systems typically lead to a form of decentralized coordination or self-organization. The components that form the decentralized system interact with each other based on local information. Out of these simple local interactions, complex global coordination can emerge if the interactions are designed well.

A decentralized coordination system operating in this manner is typically more robust and scalable than a centralized coordination system [35].

3.1.1 Vehicle Agents

Vehicle Agents represent the road users' interests in the ATIS. The agents are physically deployed on board the road users' vehicle and they have a means of communicating with the road user. This allows them to have information about the road users' destination and to present information to the road user. The Vehicle Agent acts as the interface between the AntTIS system and the road user.

The Vehicle Agent's responsibility is to provide the road user with a suitable route towards its destination. This is an ongoing responsibility. If the traffic conditions change or the predictions made by the AntTIS system change due to additional information, the Vehicle Agent has to adapt.

The agent selects the most suitable route by calculating a number of candidate routes and evaluating them using traffic forecast information. The route selection and intention revision process (Figure 3.5) is repeated before the intention propagation (Section 3.3) is repeated. Only the intention revision process takes into account previously collected information. The route selection and evaluation starts with a clean slate on every iteration.

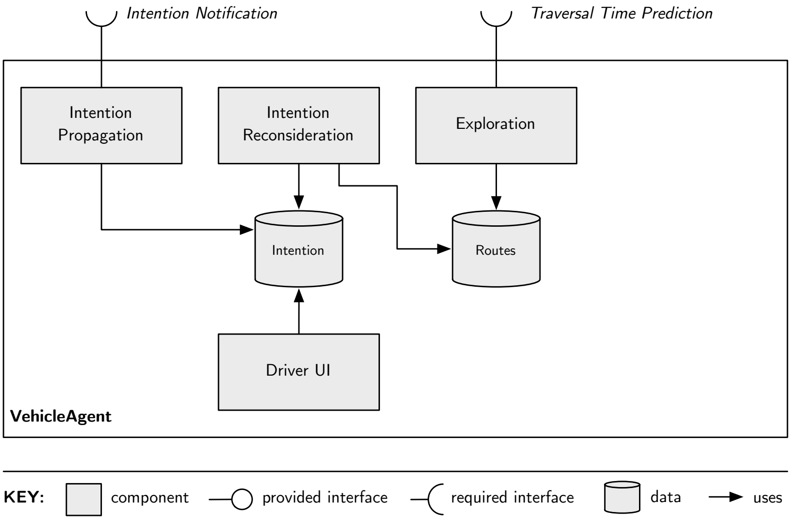


Figure 3.4: A component diagram showing the different components that make up a Vehicle Agent.

The route candidates are selected based on static traffic network information. There are multiple possible approaches to calculate a set of possible routes. A study by Bader et al. [9] lists the k-Shortest paths, Pareto, Plateau and Penalty algorithms as the most important techniques.

K-Shortest Paths and Pareto lead to candidate paths of low quality [9]. The performance of the two remaining approaches is very similar. AntTIS uses the Penalty [15] technique as it is less complicated than the Plateau technique. The Penalty algorithm is the first step shown in Figure 3.5.

The Penalty approach described by Chen et al. starts by calculating the shortest path based on the A^* algorithm. It then calculates a number of additional paths by adding a penalty to the travel cost associated with links that have been previously included in a result. The penalty is relative and in the work of Chen et al. based on the reliability of a link. In AntTIS the penalty is also relative but not based on reliability. The formula $\Delta w_i = \alpha^m(1 - r_i)^q W_0$ is thus reduced to $\Delta w_i = \alpha^m W_0$. As recommended in [15], $\alpha = 0.5$ is chosen toghether with $W_0 = 2L_{n,0}$, where $L_{n,0} = 1400sec$ is close to the mean travel time in the Flanders scenario (Section 5.4.2), and is as [15] dictates a “large value”. The factor 2 is chosen based on the recommendation made in [15] to choose W_0 somewhere in the range of $1.5L_{n,0} - 3.0L_{n,0}$.

The evaluation of these routes candidates is delegated to a separate MAS (Sect. 3.2) to alleviate the Vehicle Agent from the task of interacting with all involved Infrastructure Agents. Given the set of possible routes and their evaluation, the Vehicle Agent chooses the route that best matches the road users' desires.

Because of the dynamic nature of traffic the quality of the routes may vary over time. The Vehicle Agent continuously updates its list of possible routes and evaluates them through the dMAS. Whenever a route is sufficiently better than the one currently adopted by the road user, the Vehicle Agent will offer this information to the road user.

A Vehicle Agent that myopically changes its intention whenever it learns of a better alternative would most likely result in instability [46, 94]. Instead, the Vehicle Agents use a more stable intention revision mechanism. Upon finding a better alternative to its current intention, a Vehicle Agent will adopt that alternative as its new intention based on a probabilistic approach. The probability of adopting the alternative increases as the alternative is better than the current intention.

A probabilistic approach to changing intentions is also suggested by Hadeli [55]. The approach of Hadeli goes even further and imposes limitations on the intention revision process based on social norms (Socially Acceptable Behavior). In AntTIS, we do not impose this rate limitation, Vehicle Agents can change their intentions as often as they desire. The intention revision process is purely limited based on the quality of the available alternatives and the probabilistic limitation is there to improve the stability of the system and to offer more stable advice to the road user.

In AntTIS, the probability p of a Vehicle Agent switching to another alternative that is better is a function in the form of $p = 1 - e^{-\alpha(q-1)}$. Here q is $\frac{t_{alt}}{t_{int}}$, the travel time of the alternative route t_{alt} over the travel time of the current intention t_{int}. The parameter α is chosen to be 14. This value for α gives the following probabilities. Given an alternative route that is 5% better, q will be ≈ 1.05 and the probability p will be ≈ 0.5. This means that a Vehicle Agent has a 50% probability of switching to an alternative that is 5% better. For an alternative that is 10% better, the probability increases to almost 80%. The chosen α value thus causes only few vehicles to switch when the improvement is small and allows almost all vehicles to switch if the benefit in the improvement is significant.

By adopting the proposed route, that route becomes the Vehicle Agent's intention. Information about the Vehicle Agent's intention is shared with all relevant Infrastructure Agents using the swarm based intention propagation

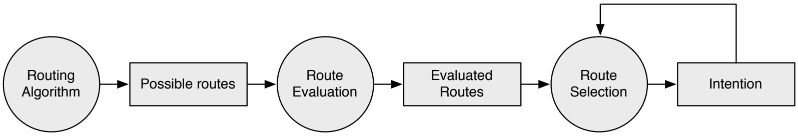


Figure 3.5: The route selection process. Routes are generated using a routing algorithm based on static road network information. Possible routes are then evaluated and the best one is selected. The route selection process takes into account the current intention and only changes intentions if a significantly better route is discovered.

(Sect. 3.3).

Key responsibilities of Vehicle Agents are:

1. Maintaining an evaluated set of possible routes to the road users' destination;
2. Informing the road user about the optimal route given current and future traffic conditions;
3. Informing all relevant Infrastructure Agents about the road users' intention.

3.1.2 Infrastructure Agents

Infrastructure Agents each represent one piece of the traffic network infrastructure. We assume Infrastructure Agents can be physically deployed sufficiently close to the traffic infrastructure element they represent to allow them to collect information about the traffic conditions on the infrastructure element and to communicate efficiently with other agents deployed physically close to the infrastructure elements location.

The Infrastructure Agent is capable of generating travel time predictions for the link it represents. It generates these predictions based on the artificial neural network approach described in Chapter 4. The training of the neural network is done using real-world travel times observed by the Infrastructure Agent and the intention levels corresponding with the time of those observations.

Using this predictive model, the Infrastructure Agents can answer queries made by the Vehicle Agents in the form of *What is the travel time for your link at*

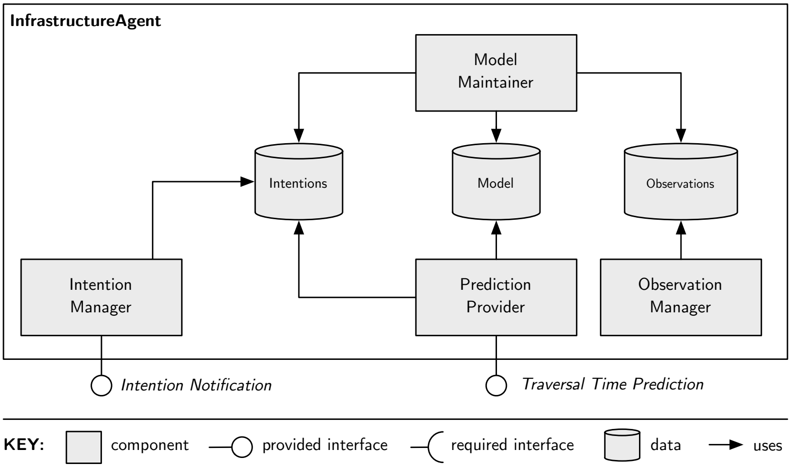


Figure 3.6: A component diagram showing the different components that make up a Infrastructure Agent.

time x. These queries allow Vehicle Agents to evaluate possible routes based on future traffic conditions (Section 3.2). A limitation of the current system is that it only takes into account travel times on roads and not intersections. Including traversal times for intersections remains future work.

A key challenge for the Infrastructure Agents is to maintain accurate intention levels for their network link. Vehicle Agents are likely to change their intentions because of changing traffic conditions. Infrastructure Agents use a form of information evaporation to ensure the intention levels they have are still accurate. Whenever an Infrastructure Agent is informed about a Vehicle Agent's intention, it will store the time at which it received this information. Later, when making predictions, the Infrastructure Agent will discard all intentions that where shared too long ago. This process requires a constant affirmation of Vehicle Agents intentions, something that is a byproduct of the swarm based intention propagation discussed in Section 3.3.

Key responsibilities of Infrastructure Agents are:

1. Maintaining a prediction model for the network link the Infrastructure Agent represents;

2. Maintaining the future intention levels for the network link the Infrastructure Agent represents.

3.2 Swarm Based Route Evaluation

The evaluation of possible routes based on their travel time is delegated by the Vehicle Agent to a MAS designed specifically for this purpose. Such delegation to specialized MASs is described in Section 2.4. The agents in this dMAS are mobile. They act as smart messages and can be forwarded between Vehicle and Infrastructure Agents. As the agents receive a route from the dispatching agent and set out to explore that route, these mobile agents are referred to as *exploration mobile agents*.

Earlier work referred to these smart messages as ants or ant agents [16, 50]. This was due to the resemblance between the resemblance in behavior between the mobile ants described in those papers and real-world ants. In this thesis, the mobile agents that form the dMAS are no longer referred to as ants. While the agents in the dMAS are still mobile, still roam the virtual environment and still use stigmergy, they no longer make their own decisions.

As shown in Figure 3.5, the set of possible routes is calculated by the agent before dispatching mobile agents to evaluate the quality of that route. As such, the mobile agents simply follow the route they are given and are not capable of making their own decisions. It is because of this reason that they are referred in this work as smart messages or mobile agents.

Upon the creation of the dMAS used to evaluate a route, the Vehicle Agent passes the route as a parameter. The dMAS will periodically dispatch a mobile agent to evaluate the route. The result of the evaluation is communicated back to the Vehicle Agent.

The evaluation goes as follows: The mobile agent is sent to the Infrastructure Agent representing the first link in the route given to the dMAS. The mobile agent queries the Infrastructure Agent asking for a link traversal time prediction given an immediate arrival at the link. Based on this prediction, the mobile agent calculates the estimated time of departure (ETD) for this link. This ETD will serve as the estimated time of arrival (ETA) for the next link.

After having the first Infrastructure Agent, the mobile agent will be forwarded to the next link in the route. Again the mobile agent queries the Infrastructure Agent, asking for a travel time prediction based on the ETA at the current link. This process continues until the mobile agent reaches the end of the route.

At that point, the last ETD received by the mobile agent is also the vehicles predicted ETA at its destination.

Having calculated the estimate time of arrival at the destination given the predefined route, the mobile agent is sent back to the Vehicle Agent and can inform the Vehicle Agent of the routes travel time.

Algorithm 3.1 describes the behavior of the mobile agent more formally. The algorithm assumes the mobile agent has a means of forwarding itself from agent to agent (the *travel_to* function) and that the mobile agent has a reference of all relevant agents in order to address them (the *origin* and *agents*[] references).

By periodically repeating this evaluation process, the Vehicle Agent's information about the route stays accurate. The periodicity is necessary because otherwise the Vehicle Agent bases its reasoning on stale information. The evaluation of candidate routes is the only way the Vehicle Agent receives information on routes other than its current intended route. Whenever the Vehicle Agent looses interest in a route, it halts the dMAS responsible for evaluating that route.

```
Require: Reference origin to the originating Vehicle Agent
Require: The route to be evaluated: a list link[] of links
Require: List agents[] of refs to the Infrastructure Agents responsible for link[]
  time_horizon ← current_time
  position ← position_VA
  i ← 0
  repeat
    travel_to(agents[i])
    travel_time from agent[i]
    time_horizon ← time_horizon + travel_time
    position ← endpoint_of(link[i])
    i ← i + 1
  until position == destination_VA
  travel_to(origin)
  notify Vehicle Agent of time_horizon for link[]
```

Algorithm 3.1: The behavior of a mobile agent evaluating a route. The algorithm requires a function allowing the mobile agent to travel from agent to agent: the *travel_to*() function. It also requires references to all relevant Infrastructure Agents (*agents*[]) and a reference to the Vehicle Agent that dispatched the mobile agent (*origin*).

Using a dMAS to handle the evaluation of all interesting routes relieves the Vehicle Agent from this ongoing concern. It encapsulates this responsibility of the Vehicle Agent.

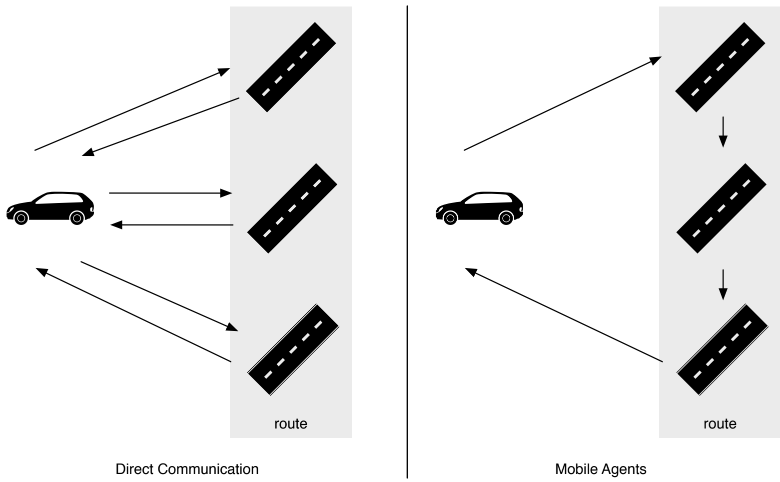


Figure 3.7: The difference between using direct messages (left) and mobile agents (right) to communicate between Vehicle Agent and Infrastructure Agent.

The use of mobile agents travelling from Infrastructure Agent to Infrastructure Agent also reduces the overall communication cost needed to evaluate the routes. If the Vehicle Agent would query all Infrastructure Agents, it would require $2 \times n$ messages, where n is the number of links in the route. As the Vehicle Agent would have to send a request to each Infrastructure Agent individually, await the reply, calculate the next ETA in order to query the next Infrastructure Agent. If we take a mobile agent to be the equivalent of one such message, the number of messages is only $n + 1$. One message to each Infrastructure Agent and a final message back to the Vehicle Agent.

The use of mobile agents has a second benefit regarding the necessary communication. It reduces the communication bottleneck at the Vehicle Agent. With the mobile agent roaming through the virtual environment, not all messages have to go back and forth to the Vehicle Agent. Assuming communication between Infrastructure Agents is cheaper than communication between Infrastructure Agent and the mobile Vehicle Agent, this shift in communication is even more significant.

Key benefits of using a dMAS consisting of mobile agents to evaluate the possible routes are:

1. The responsibility of informing Infrastructure Agents about the road users intention is encapsulated;
2. Using a mobile agent reduces the communication cost and bottleneck.

3.3 Intention Propagation

Vehicle Agents need to share their intentions in order to allow Infrastructure Agents to make travel time predictions. The challenges this poses for Vehicle Agents resembles those posed by the evaluation process described in the previous section. The solution is therefor very similar: Vehicle Agents delegate the responsibility of informing all relevant Infrastructure Agents to a dMAS.

The mobile agents in this dMAS, referred to as *intention mobile agents*, behave similarly to the ones used to evaluate a possible route. The main difference lies in the additional interaction between the mobile agent and the Infrastructure Agent and the fact that the mobile agents responsible for intention propagation will only be dispatched on the road users current intention.

Intention mobile agents traverse the virtual environment equivalent of the route the road user intends to follow. Just as the exploration mobile agents did for possible routes. The intention mobile agents arrive at an Infrastructure Agent, they interact with the Infrastructure Agent to obtain the travel time and the ETD just as the evaluation mobile agents do. But in addition to obtaining this information from the Infrastructure Agent, the intention mobile agent also informs the Infrastructure Agent that the vehicle it represents will traverse the link the Infrastructure Agent represents between the ETA and the ETD for that link.

Algorithm 3.2 more formally describes the behavior of the intention mobile agent.

The use of intention mobile agents means no evaluation mobile agent is needed to evaluate the current intention of the road user, as the evaluation is a byproduct of the intention propagation process.

Intention mobile agents are likely to be sent out more frequently because the information they convey is discarded by the Infrastructure Agent after a delay (Sect. 3.1.2). Intention mobile agents must be continuously dispatched to confirm the road users intention is unchanged. Changes in the road users intention require no communication or mobile agents to remove information about the old intention from the Infrastructure Agents. The evaporation process will make sure the information is quickly discarded.

Require: Reference *origin* to the originating Vehicle Agent
Require: The current intention: a list $intention[]$ of links
Require: List $agents[]$ of refs to the Infrastructure Agents responsible for $intention[]$

$time\_horizon \leftarrow current\_time$
$position \leftarrow position_{VA}$
$i \leftarrow 0$
repeat
  $travel\_to(agents[i])$
  $travel\_time$ from $agent[i]$
  $notifyagent[i]$ of visit between $time\_horizon$ and $time\_horizon + travel\_time$

  $time\_horizon \leftarrow time\_horizon + travel\_time$
  $position \leftarrow endpoint\_of(intention[i])$
  $i \leftarrow i + 1$
until $position == destination_{VA}$
$travel\_to(origin)$
notify Vehicle Agent of $time\_horizon$ for $intention[]$

Algorithm 3.2: The behavior of a intention mobile agent. The algorithm requires a function allowing the mobile agent to travel from agent to agent: the $travel\_to()$ function. It also requires references to all relevant Infrastructure Agents ($agents[]$) and a reference to the Vehicle Agent that dispatched the mobile agent ($origin$).

Key benefits of using a dMAS consisting of mobile agents to propagate the road users intention to all relevant Infrastructure Agents are:

1. The responsibility of informing Infrastructure Agents about the road users intention is encapsulated;
2. Using a mobile agent reduces the communication cost and bottleneck.

3.4 Conclusion

This chapter described the AntTIS system used to assess the potential of dMAS in traffic. A route guidance system using anticipatory traffic information to better guide road users towards their destination.

The AntTIS system is based on *MAS* architecture with two types of agents: *Vehicle Agents* and *Infrastructure Agents*. Both agents are situated in a Virtual Environment allowing them to interact through communication. Vehicle Agents are deployed on-board road users vehicles and move through both the real-world and the Virtual Environment. In the real world, Infrastructure Agents are deployed in proximity to the road network link they represent. In the Virtual Environment, Infrastructure Agents are positioned on the network link they represent.

The Vehicle Agents delegate certain responsibilities, namely evaluation of route candidates and the propagation of the current intention to a dMAS. Mobile agents in these dMASs traverse the virtual environment and interact with other agents on behalf of the delegating Vehicle Agent. Delegating these two responsibilities nicely encapsulates the functionality. The use of mobile agents reduces the overall communication cost needed for the inter-agent interactions and reduces the communication bottleneck at the Vehicle Agent.

Infrastructure Agents use a prediction model they train online to provide ad hoc predictions to Vehicle Agents. It is through these predictions that Infrastructure Agents try to maintain favourable traffic conditions on the link they are responsible for.

The use of dMAS helps us in dealing with the challenges mentioned in the Introduction (Section 3.1) of coordinating a system as large and dynamic as traffic. The use of mobile agents limits the interactions between Vehicle and Infrastructure Agents by taking advantage of the fact that interactions between the two types always occurs along a possible route. A mobile agent following this route through the Virtual Environment (Figure 3.3) is not required to travel back to the Vehicle Agent before interacting with the next Infrastructure Agent on its path.

The architecture discussed in this section is complemented by a machine learning technique discusses in the following chapter (Chapter 4). It is the introduction of machine learning to handle the information on the Infrastructure Agent side together with the route evaluation discussed in this chapter than allows the AntTIS system to apply the dMAS technique in traffic coordination.

Chapter 4

Intention based Short Term Traffic Predictions

AntTIS is an anticipatory system. It continuously estimates future traffic conditions and uses these forecasts to guide its users in choosing better routes.

The anticipatory nature of AntTIS allows the system to not just react to changing traffic conditions, but to forecast and prevent such unwanted changes if possible. If congestion is forecasated and faster alternatives are available, the AntTIS system will direct the driver away from the congestion, thus delaying the congestion buildup. This is only possible as long as there are better alternatives. If there are no better alternatives, the congestion will not be avoided as drivers will be directed towards the fastest alternative.

This chapter describes how these forecasts are generated. The forecasting mechanism builds upon the use of delegate multiagent systems (dMASs) as a coordination mechanism [50, 48]. Van Parunak also uses a similar mechanism called *Polyagents* to deal with the future and with future uncertainty [65, 67].

The approach described in this section evolved from the early work on dMASs as a coordination mechanism in manufacturing control. In that coordination mechanism, dMASs are used to reserve future timeslots in resources. By analyzing all reservations for a resource, the system can forecast its future use. This is the same notion of forecasting we utilize in AntTIS.

The delegate multiagent coordination mechanism was first applied in a traffic scenario in the 2007 paper by Weyns et al. [103]. In this work, the forecasting mechanism still relies on the concept of reservations. Meanwhile, related research

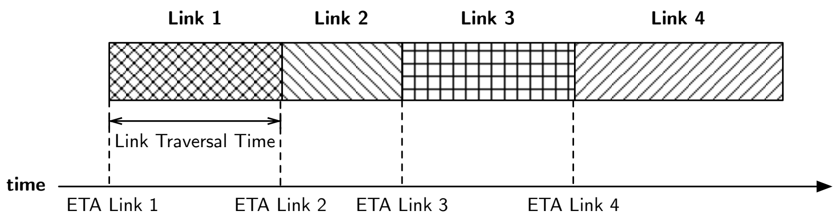


Figure 4.1: Schematic representation of the intention of one road user. This road user intends to reach his destination by traversing *Link 1*, *Link 2*, *Link 3* and then finally *Link 4*. The intention also contains the ETAs for every link in the sequence and thus also the expected link traversal times.

was advocating abandoning reservations in traffic as they are too brittle and unrealistic [79, 33, 34].

The reservation based system in AntTIS was abandoned and a number of alternatives were explored [18]. Finally, an approach based on artificial neural networks (ANNs) proved to be the easiest and most robust solution [19]. It is this approach that is described in the remainder of this chapter.

Overview This chapter starts by explaining where the information that is used to make the predictions originates. This is done in Section 4.1. The next section, Section 4.2, discusses how information from different road users is aggregated and kept up-to-date. In Section 4.3 the use of neural networks to map user intentions on link traversal times is explained. Finally, Section 4.4 concludes.

4.1 Intention Propagation

The AntTIS system relies on Infrastructure Agents being able to predict future link traversal times as described in Section 3.1.2 and 3.2. The information on which these forecasts are based is provided by the community of road users participating in the AntTIS system.

Every road user has *an intention*. This intention is the route he intends to follow to reach his destination. An intention includes the sequence of links the road users intends to traverse along with the estimated time of arrival (ETA) for every one of these links (Figure 4.1).

Based on the combined intentions of all road users, the number of vehicles on every link at any time in the future is known beforehand. That is assuming the following assumptions holds true:

1. All road users that will be present in the traffic network at the predicted time should have already made their intentions known.
2. All road users must stick to their intentions and follow the sequence and timing of the intention.
3. The ETAs contained in the intentions should be accurate.

These three assumptions will never hold in a realistic setting. However, to illustrate how the forecasts are generated and on what information they are based, we will temporarily assume these assumptions to be true. Further along this section, we discuss how these assumptions can be weakened until they can be achieved in realistic settings and still lead to meaningful predictions.

The number of vehicles on a traffic link l at a future point in time t can be determined by counting the intentions that have an ETA less than or equal to t for that link and an ETA larger than or equal to t for the next link in the sequence of links (Figure 4.2).

These vehicle counts can be used to *estimate* future link traversal times for a link. The time it takes a vehicle to traverse a link starting at time t_i will be dependent on the vehicle counts at t_i, t_{i-1}, t_{i-2}, ..., t_{i-n}[1]. Here the interval t_i - t_{i-n} is the time in which vehicles that affect the traversal time of the vehicle enter the link (Figure 4.3).

The predictions made by the AntTIS system are based on the information contained in the intentions of the road users. Contrary to many other [29, 89, 85, 91] traffic forecasting systems, AntTIS does not extrapolate from the current traffic conditions in order to compute a traffic forecast. The information contained in the road users' intentions is not an extrapolation. It is actual information about the future state of the traffic network. This information is mapped onto link traversal times.

The predictive power of the system lies in the propagation and aggregation of the intentions. Instead of extrapolating information about individual traffic links forward into time, the AntTIS system takes information that already describes the future of those links and transforms that information into link traversal time information.

[1] This assumes vehicles are able to leave the link freely, i.e. that there is no congestion blocking the outflow of vehicles.

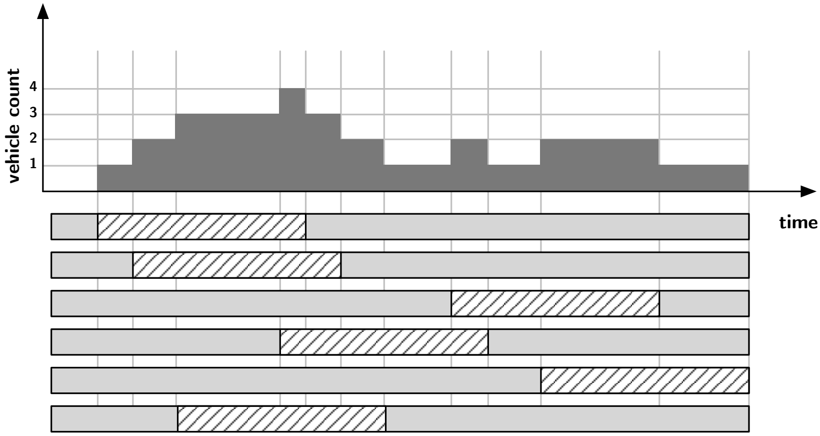


Figure 4.2: Schematic representation of how the vehicle counts can be determined based on the information in intentions. The bars at the bottom of the represent the intentions. Other links in the intentions are left grey. Only the link for which we want to calculate the vehicle counts is marked. The graph at the top of the figure shows the vehicle count over time.

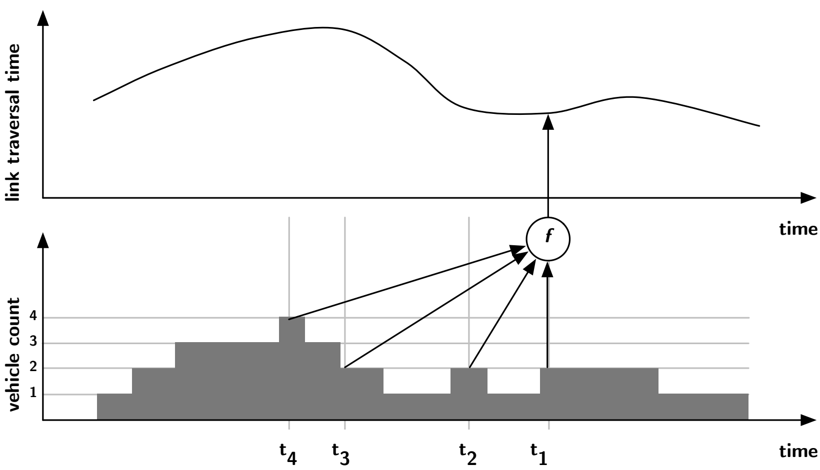


Figure 4.3: Schematic representation of the calculation of the link traversal time based on the vehicle counts. Here the traversal time at time t_1 is calculated using a function f with as input parameters the vehicle counts at times t_1, t_2, t_3 and t_4.

The assumptions made earlier in this section still need to be addressed. Going forward in the description of the prediction process, we will no longer assume they hold. This leads to the following challenges that need to be addressed in order to use the forecasting mechanism described above.

Key Challenges

1. **Information freshness** Traffic conditions are dynamic and will change over time and road users will change their intentions based on the information they receive and observe. The system should not assume intentions are fixed, nor should it place the responsibility of maintaining the information freshness on the road users.
2. **Participation rate** We should not assume all drivers participate in the system. If a system such as AntTIS is ever to be deployed in the real-world, it should function even when only a portion of the road user participate, otherwise it will never be adopted.
3. **Forecasting accuracy** The intentions that serve as input to the forecasting process also contain information based on the forecasting process. As long as the forecasting is accurate enough the ETAs will be correct and the vehicle counts will be be a good estimation of the actual future vehicle count. Inaccurate ETAs will lead to small incorrections in the vehicle count which could lead to inaccurate link traversal times.

How these challenges are addressed is described in the remainder of this chapter.

4.2 Intention Aggregation and Evaporation

The previous section describes how intentions can be used to determine vehicle counts. It started off with a number of assumptions and ended with the challenges that need to be overcome in order to drop or loosen those assumptions. This section describes how the Infrastructure Agents described in Section 3.1.2 manage the information contained in the intentions.

4.2.1 Aggregation of the Intentions

When receiving an intention from a road user, the Infrastructure Agent records the following information:

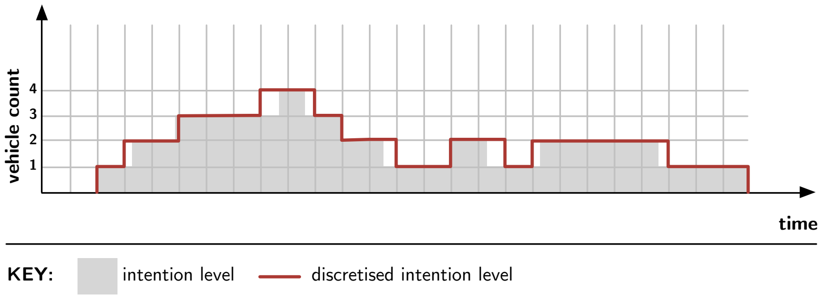


Figure 4.4: The intention levels are stored for a discretized time. For every time interval, the intention levels are aggregated and stored.

VehicleId To ensure correct handling of the intention, the intention contains an identifier that identifies the Vehicle Agent responsible for that intention.

Estimated Time of Arrival The ETA is used by the Infrastructure Agent to keep track of the intention levels.

In addition to this information provided by the smart message delivering the intention to the Infrastructure Agent, the Infrastructure Agent will also calculate the estimated time of departure (ETD) for the vehicle.

To facilitate storing the intention levels, the intention levels are aggregated based on time. The Infrastructure Agent discretizes time into intervals and maintains one intention level for every one of these intervals (Figure 4.4). This allows the Infrastructure Agent to quickly determine the intention level for any point in time without loosing too much in terms of accuracy.

The width of the time intervals is set to 5 seconds, a value that still ensures sufficient granularity.

4.2.2 Evaporation of the Intentions

The intentions of the road users are dynamic. Road users can change their intentions over time as the traffic conditions evolve and the road users receive additional information.

It is the responsibility of the Infrastructure Agent to maintain accurate intention levels. In order to do this, the Infrastructure Agent requires regular updates from the Vehicle Agents. If a Vehicle Agent fails to reconfirm its intention to visit the Infrastructure Agent, the Infrastructure Agent will disregard the intention previously received from the Vehicle Agent.

This discarding of information ensures that the intentions that are contained in the intention levels are all still relevant. If any of the intentions becomes irrelevant, it only takes a while before it is discarded.

This behavior of the Infrastructure Agent places the burden of maintaining the intentions with the Vehicle Agents. It is now their responsibility to reconfirm their intentions on a regular basis with all involved Infrastructure Agents.

This has benefits for the Vehicle Agents as well. By updating their intentions and sending a smart message over the route they intend to follow, the Vehicle Agents receive updates on their estimated arrival time at their destination. Should this ETA change, the Vehicle Agents can compare with alternative routes and change its intention. It no longer needs to inform the Infrastructure Agent of the change, the stale information will be discarded over time.

When an Infrastructure Agent receives an intention from a Vehicle Agent, it records the attributes as mentioned in the previous section and updates the intention levels. It will also record the arrival time of the smart message. This information is later used to decide whether an intention is still up to date or whether it can be safely discarded.

When an Infrastructure Agent receives an intention from a Vehicle Agent it first checks whether there is a still valid intention from that Vehicle Agent contained in the intention levels. If there is an intention present, it is removed from the intention levels to prevent counting one intention multiple times.

The lifetime of an intention, the time before it is discarded, is closely related to the interval with which the Vehicle Agents reconfirm their intentions. The lifetime should be slightly higher than the refresh interval. Otherwise intentions are discarded before they can be reconfirmed. The difference between the two times should not be too large, as that would increase the time stale intentions remain relevant for the Infrastructure Agent. The difference should be determined based on the time it takes for the smart messages sent out by a Vehicle Agent to reach all Infrastructure Agents.

Choosing the refresh rate for the intentions is making a trade-off between communication overhead and information accuracy. A short intention lifetime means Vehicle Agents need to frequently reconfirm their intentions. A long intention lifetime means it takes some time before stale intentions are discarded.

AntTIS currently uses a value of 1 minute as the refresh rate for intentions. Vehicle Agents sent out intention smart messages over their intended route every minute. Infrastructure Agents maintain the intention levels for 2 minutes.

After this time time, intentions that are not reinforced are discarded. While the GridLock simulation platform also simulates asynchronous and time delayed communication between agents, these intervals are chosen empirically based on the simulated communication and will have to be adjusted based on the characteristics of the communication network used.

4.3 Artificial Neural Network based Traffic Predictions

This section describes ANNs and how AntTIS uses ANNs to calculate link traversal predictions based on the aggregated intention levels. Contrary to many other traffic state prediction mechanisms relying on ANNs, AntTIS does not use the ANNs for their predictive capabilities. AntTIS relies on the intention propagation to predict the intention levels and uses ANNs to map those predictions onto link traversal times.

ANNs based forecasting approaches can generally be divided into two categories: time series models and causal models. In time series models the predictions are based on a function of past observed values. Here the ANN is used to approximate the function that describes how a time series evolves based on its current and past states. In causal models the predictions are based on exogenous factors and ANNs are used to approximate the function that describes the prediction based on observations or predictions of the external variables.

The approach taken by AntTIS is the causal model. Link travel times are influenced by the presence of vehicles on the road. Information about the presence of vehicles on the road is contained in the intention levels maintained by the Infrastructure Agent. The ANNs are used to map the intention levels onto link traversal time predictions.

The input of the ANN does however somewhat resemble the input in the time series model. In time series model, the inputs for the ANN are typically lagged observation values. The ANN can be written as a function f, where $y_p = f(y_0, \ldots, y_i)$. The y_i values represent past observations of the variable that is being predicted in y_p. In AntTIS, the structure is similar. The majority of the input variables to the ANN are lagged intention levels. Values of the intention levels at various times prior to the point in time we are predicting a value for. Contrary to the time series model inputs, where all y_i values are actual observations that occur in the past, the intention level inputs used in AntTIS can describe past or future points in time.

The approach presented in this thesis is therefore not dependent on ANN. Any other mechanism that is capable of mapping the intention levels onto the link traversal times can be used. The decision to use ANNs is due to the interesting properties described in the remainder of this section.

Predictions are made by the Infrastructure Agents. Every Infrastructure Agent has local access to the intention levels it received from the Vehicle Agents. When an Infrastructure Agent receives a link traversal time query for a future point in time from a smart message it evaluates its model, an ANN, to calculate the future link traversal time. These artificial neural networks are maintained by the Infrastructure Agent.

The remainder of this section provides more background information on ANNs and how they are used by the Infrastructure Agents to map the aggregated intention levels onto link traversal time predictions.

4.3.1 Artificial Neural Networks

The predictions generated by an Infrastructure Agent are based on the intention levels aggregated by that Infrastructure Agent. The intention levels are an indication of the future traffic state, they represent the number of vehicles that have confirmed to be present on the link at a future point in time. However, as was shown in Figure 4.3, predicting link traversal times still requires mapping these intention levels onto link traversal times. This mapping is done using ANNs.

ANNs are computational models that can compute a number of output values based on a (possibly) large number of input values. An ANN consists of a number of interconnected *neurons*. The structure and functioning of ANNs is modelled after an animals central nervous system.

In a central nervous system many neurons form a directed graph. Every neuron can be *activated* if receives sufficient input through its dendrites. If a neuron activates, it emits a signal through its axon. This signal can serve as the input to other neurons, and can cause their activation if they have sufficient input.

ANNs operate in a similar fashion. It is also structured as a directed graph. Every neuron in the graph receives input from other neurons. The input coming from other neurons is typically multiplied by weights. The weighted input is evaluated using an activation function. If the activation function reaches a certain threshold, the neuron is activated. Its output is then calculated and can go on to trigger other neurons further along the graph. A schematic representation of a neuron is shown in Figure 4.6.

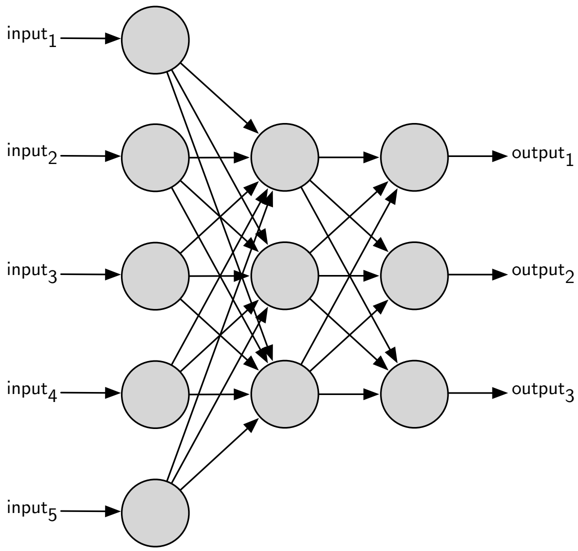


Figure 4.5: A schematic representation of an ANN. The ANN in the picture calculates three output values based on five input values. This network consists of three layers of neurons. The first layer on the left is triggered directly by the input values, the output values of the last layer on the right serves as the output.

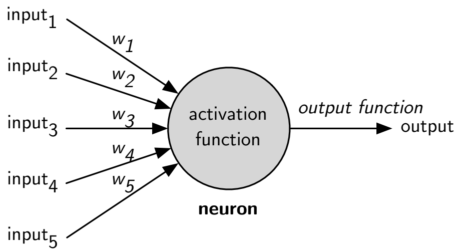


Figure 4.6: A schematic representation of a single neuron. This neuron has 5 inputs each weighted with a weight factor. The neuron has an activation function that evaluates the inputs. If the activation threshold is passed, the neuron will activate and the output will be calculated based on the output function.

By adjusting the weights of an ANN, the network can be altered to approximate different functions. The adjusting can be automated to *train* an ANN to approximate an unknown function based on known input and output values for that function.

ANN are being widely used in forecasting [114]. There are several distinguishing features of ANN that make them suitable for forecasting. ANN are data-driven. There is no need to build a model for the problem being studied. The implicit model provided by an ANN is self-adaptive. Through training, the model will adapt itself to the observed reality. Thus, ANNs are good candidates to problems where the model is hard to specify, but where sufficient real-world data is available [114].

In AntTIS we use ANNs as function approximations. In order to generate predictions the system maps information in the intention levels onto link traversal times. ANNs are universal function approximators. It has been shown that an ANN can approximate any continuous function to a desired accuracy [53, 39]. Besides being universal function approximators, ANNs can generalise. Based on only partial observations, ANNs are often able to infer the unseen part of the relation. Even if the partial observations are noisy.

The use of ANNs in forecasting is not new. It is the introduction of the backpropagation algorithm [71, 101] that enabled widespread use of ANNs and that enabled a lot of research into ANNs and their use in forecasting [63, 47, 114]. Several studies show that ANN based forecasting outperforms traditional statistical methods, even for nonlinear time series [101, 60].

The widespread use of ANNs in machine learning means there are a lot of robust implementations available. The AntTIS system can benefit from these libraries that are developed and tested elsewhere.

It is because of these properties that we use Artificial Neural Networks to map the intention values onto the link traversal times [19]. The aggregated intention levels serve as the input for the artificial network, the link traversal time is the output of the network.

ANNs are not an essential component of the AntTIS system. As mentioned above, they are a flexible and convenient way to map the intention levels onto link traversal times. There are however some drawbacks to using ANNs.

ANNs are prone to overfitting. When the structure of the ANN is too complex the ANN loose their ability to generalize. Instead, the ANN will start to include noise on the training data into the model. Therefore, in AntTIS the size of the ANNs is kept to a minimum as discussed in Section 4.3.2.

A second disadvantage of ANNs is the lack of guidance in choosing a suitable structure for the ANNs. This means the structure and number of neurons has to be determined empirically.

Despite these drawbacks to ANNs, AntTIS uses ANNs instead of alternatives such as support vector machines and statistical learning models because of the flexibility, robustness and ease of use.

The ANNs implementation used in AntTIS is Neuroph. A robust implementation of ANNs in Java[2]. Neuroph is available both as a desktop application and a software library. The desktop application facilitates the empirical determination of a suitable network size.

4.3.2 Structure of the Artificial Neural Networks

The ANNs used in the AntTIS system are feedforward MLP. MLPs are used in various problems especially in forecasting because f their capability of arbitrary input-output mapping [114].

The graph structure of a *feedforward* ANN does not include any cycle. In a feedforward ANN information always moves in one direction. The ANN shown in Figure 4.5 is an example of a feedforward ANN. ANNs in which the graph structure does contain cycles are called *recurrent*. Recurrent neural networks have temporal behavior. Results calculated by the network can depend on output values calculated earlier on. Recurrent neural networks are often used in traffic prediction where they are used to extrapolate a timeseries into the future [29, 89].

The graph structure of a multi-layer artificial neural networks is built up out of a number of layers. The neurons in one layer are not interconnected. Instead they are only connected to the neurons in the layer preceding and following that layer. Figure 4.7 shows the structure of a multi-layer neural network. The layer whose neurons are connected to the input values is called the *input layer*. The layer of neurons that provides the eventual output values is called the *output layer*. Layers in between are called hidden layers. Their number and size does not affect the dimensions of the input and output values. The complexity of the function an ANN can approximate is affected by the size and number of hidden layer. More and larger layers allow for approximating more complex functions.

In the AntTIS system we use feedforward neural networks with one hidden layer. The output layer consists of a single neuron whose output will determine the predicted link traversal time. The size of the input layer determines the

[2]http://neuroph.sourceforge.net/

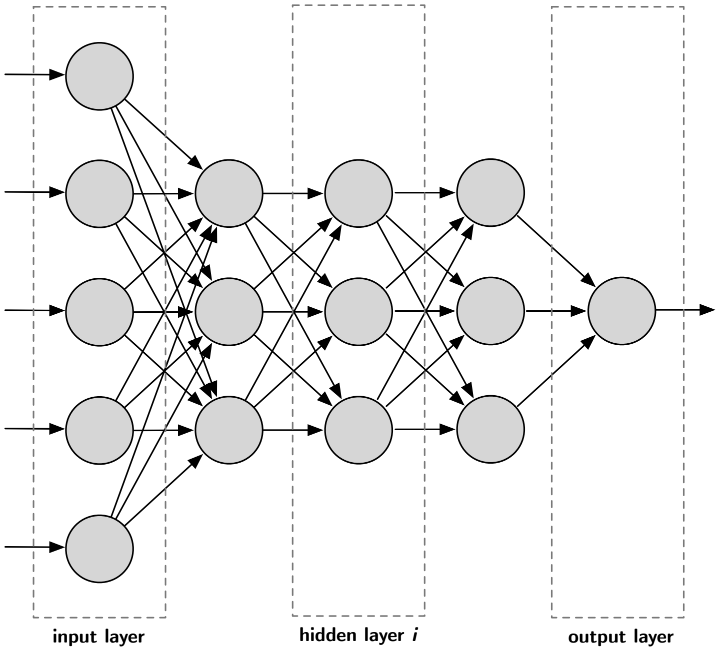


Figure 4.7: ANNs are often structured in layers. The numbers of neurons in the input and output layer determine the dimensions of respectively the input and output data. The number of hidden layers and the number of neurons in each of the hidden layers affects the complexity of the function the ANN will be able to represent.

number of intention levels that is taken into account when calculating the link traversal time.

The inputs for the ANN when calculating the link traversal time at time t are defined as follows:

$$input_0(t) = intention\_level(t) \tag{4.1}$$

$$input_i(t) = intention\_level(t - \delta^{i-1}) \tag{4.2}$$

Here $input_i$ serves as the input for the i-th input neuron. $intention\_level(t)$ is the intention level currently stored for future time t. By subtracting an ever growing interval from t we make sure to account for intention levels occurring before the future time t. If there are n neurons in the input layer, then the

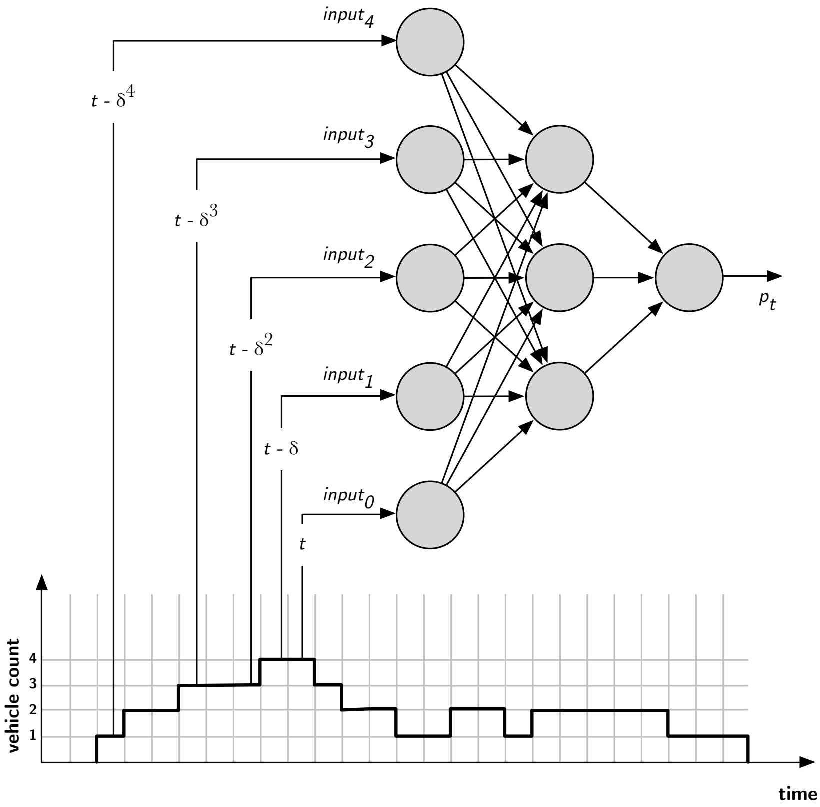


Figure 4.8: The intention levels maintained by the Infrastructure Agent serves as input to the artificial neural network. Based on these intention levels the artificial neural network calculates the link traversal time. The input levels at t, $t-\delta$, $t-\delta^2$, $t-\delta^3$ and $t-\delta^4$ serve as input when the neural network must calculate the prediction p_t at time t.

combination of n and δ determines how far back the intention levels are taken into account and how much of the past levels are taken into account (Figure 4.8).

In designing a MLP one must determine the following variables [114]:

The number of the input nodes. The number of input nodes is typically determined by the number of variables the function being approximated is defined over. In the case of MLP used in AntTIS, the inputs are determined by the number of intention levels taken into account (Figure 4.8) and the information provided by other links (Section 4.3.4).

The number of hidden layers and hidden nodes. The number of nodes in the hidden layers determine the flexibility of the approximator. The more nodes in the hidden layer, the more complex the functions that can be approximated. The downside of having more hidden layers and more hidden nodes is that the generalization capabilities of the MLP are reduced and that it becomes harder to train the MLP.

The number of output nodes. Here there is no room for design choice in AntTIS. The MLP approximates an univariate function. There is only one output: the predicted link traversal time.

There exist many approaches that help in the design process. However, these methods are quite complex in nature and difficult to implement, furthermore non of these methods can guarantee the optimal solution for a real forecasting problem [114]. The only guidelines for the design are either heuristic or based on simulations and experimentation. Zhang et al. even call the design of an ANN “more of an art than a science” [114].

Determining good values for n and δ is the result of off-line analysis. These values serve as configuration parameters to the AntTIS system. An empirical study has shown that an input layer consisting of 8 input neurons and 17 neurons in the hidden layer leads to ANNs capable of modelling the relationship between the intention levels and the link traversal times, while still not too complex to train efficiently using backpropagation [19].

Theoretical work shows that a single hidden layer is sufficient for an ANN to approximate any complex nonlinear function [51]. Therefore most ANN designs for forecasting only have one hidden layer. A second hidden layer may reduce the number of hidden nodes required in the single hidden layer approach, thus reducing the overall network size and training time. In our empirical search for a suitable design for the AntTIS MLP this benefit was not so clear and the single hidden layer design was kept.

An overview of ANN designs used in forecasting compiled by Zhang et al. in [114] show that most designs feature a single hidden layer and have on average ≈ 12 hidden nodes in that layer. None of the networks have more than 24 nodes in one layer. These observations correspond with the findings in our study [19].

In determining how far back the inputs have to be included as inputs, the average length of the links should be taken into account. Link traversal times on long links are likely to be influenced by a larger interval of intention levels. The average link traversal time should be less than δ^{n-1}. In our experiments we choose δ_l for link l based on the static link traversal time for that link. The static link traversal time is the time it would take to traverse the link at the speed limit.

$$\delta_l = \sqrt[n-1]{static\_ltt_l} \tag{4.3}$$

4.3.3 Training of Artificial Neural Networks

The ANNs are trained by the Infrastructure Agents based on observations they make. In AntTIS we assume that Infrastructure Agents have access to observations made on the road they represent. Infrastructure Agents monitor how long it takes a vehicle to traverse the road. This link traversal time is then used to train the ANN maintained by the Infrastructure Agent.

The training values has the intention levels known to the Infrastructure Agent as input values and the observed link traversal time as the output value.

This automated online learning has a number of advantages. It ensures that the designers of the system do not need to model every road individually. The learning process also ensures that artificial neural networks take into account the partial participation of road users from the beginning.

The fact that the intention levels obtained by the Infrastructure Agent are only a fraction of the intention levels that the agent would have received if every road user would participate. The ratio of participating road users is therefore implicitly learned by the ANN. If adoption of the AntTIS system increases (or decreases) the online learning ensures that the ANN continues to take this dynamic ratio in to account.

4.3.4 Interconnecting Artificial Neural Networks

This section has described how the ANNs use the intention levels to predict link traversal times. This assumes that the link traversal times of a link are only dependent on the traffic entering that link. In real-world traffic networks this is not the case.

Link traversal times are influenced by both the inflow of vehicles at the start of a link, but also by the outflow of vehicles at the end. If vehicles are unable to exit the link, for example due to congestion further downstream.

As long as congestion can be avoided, the information present in the intention levels will suffice to calculate the link traversal times. If congestion does occur, it has to be taken into account.

Infrastructure Agents can learn when their link becomes congested and the inflow of vehicles from upstream links will halt. By monitoring speed and vehicle inflow and relating this with the intention levels registered at that point, they can start learn when the link becomes congested based on the intention levels that the Infrastructure Agent receives. The Infrastructure Agent thus learns a threshold for the intention levels, that when reached, indicates that the link is saturated.

When Infrastructure Agents know they will become congested at a future point in time, they will inform the Infrastructure Agents upstream (Figure 4.9). In the Infrastructure Agents upstream, this information complements the information already present in the intention levels. It is also kept for the same discretized time and is also subject to evaporation if it is not reinforced regularly.

The information is shared with the upstream Infrastructure Agent through message passing. The information is only sent to the Infrastructure Agents representing the links directly connected to the Infrastructure Agent reporting the future congestion. As the interactions involve far less entities than the exploration of the network or the intention propagation, the use of a dMAS dedicated to this interaction is not necessary. The information shared with the upstream Infrastructure Agents is limited to a boolean value indicating that there is congestion.

For the evaporation rate of the congestion information, the same value as for the intention levels (Section 4.2.2) is chosen. As the messages that convey the congestion information are sent when the intention levels change, the frequency of congestion updates is at least that high.

These downstream congestion levels also serve as input to the ANNs. By leveraging the flexibility of the modelling capabilities of the ANNs and the

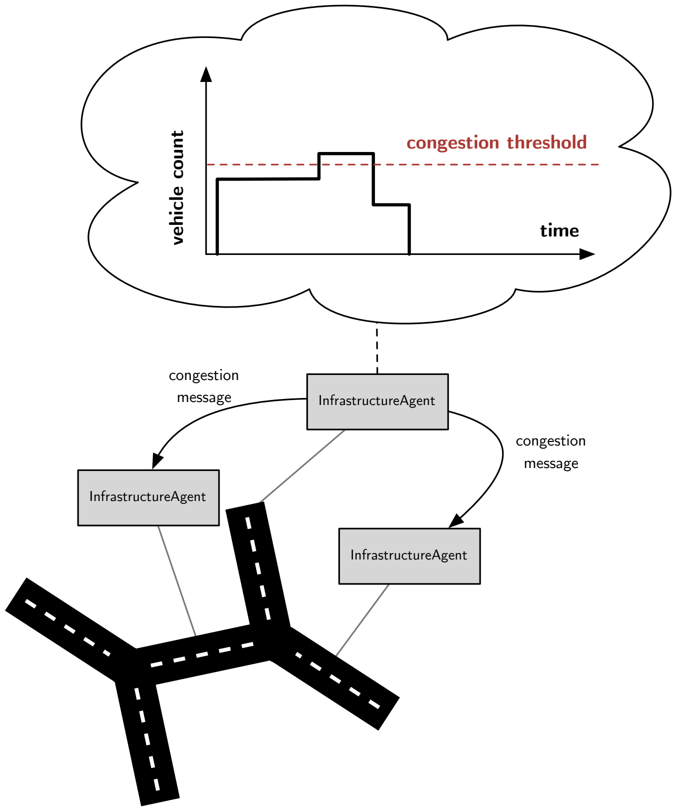


Figure 4.9: Intention Agents monitor the intention levels. If the congestion threshold is reached, the Intention Agent will inform upstream agents of future congestion through direct messages.

training process, the downstream congestion information can be integrated with the intention levels and can contribute to the calculation of the link traversal times.

The additional information affects the structure of the artificial neural networks. The number of layers remains the same. One input layer, one hidden layer and one output layer. The size of both the hidden and input layer are increased to incorporate the additional inputs (Figure 4.10).

The need for congestion information from downstream links breaks the locality principle. Without it, the Infrastructure Agents only dealt with local information, assuming that only that information affected the link traversal

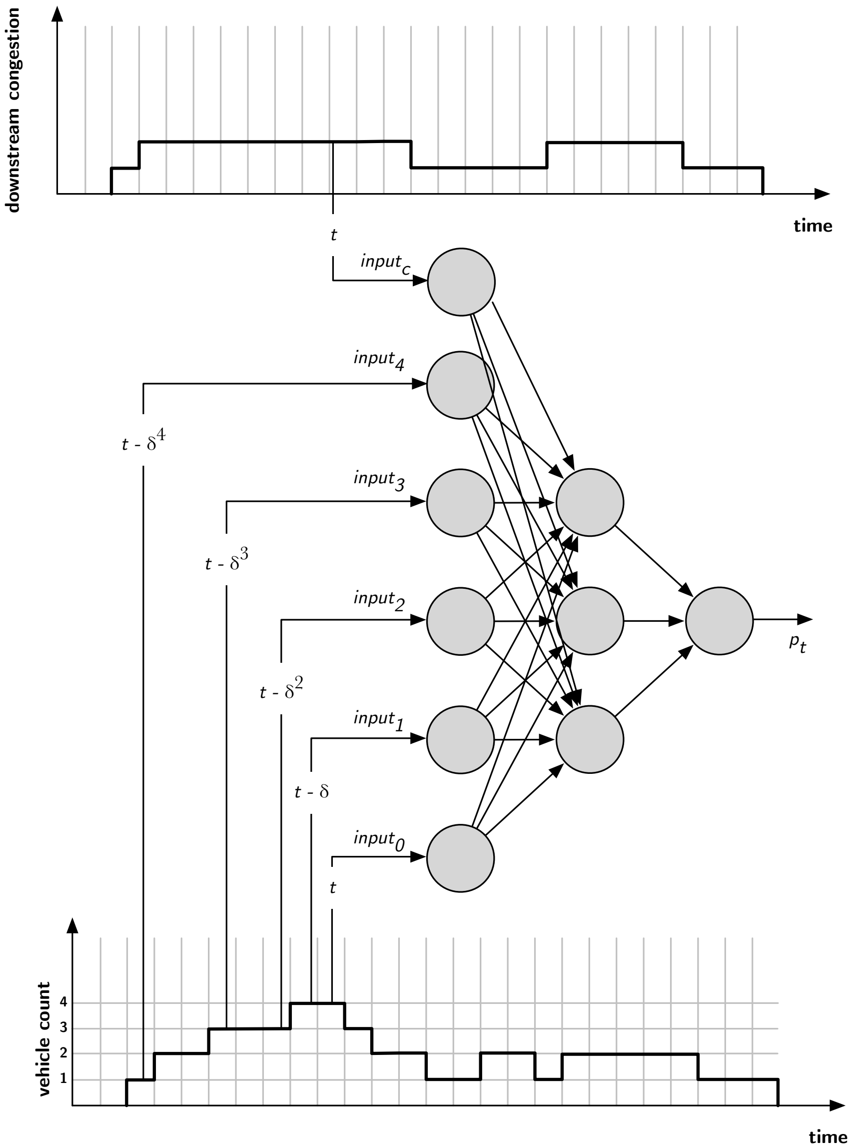


Figure 4.10: To take downstream congestion into account, the ANNs also need to take into account information about that congestion. The information provided by the Infrastructure Agents downstream is combined with the intention levels and serves as input to the artificial neural network

times experienced by the road users. By limiting the information exchange to only the directly connected links, the complexity of the information exchange is limited while information about congestion is still allowed to trickle down the traffic graph.

4.4 Conclusion

This section describes how intention propagation by the Vehicle Agents leads to Infrastructure Agent knowledge about future intention levels. These future intention levels can then be used by the Infrastructure Agents as input to the ANNs that they maintain. The output of the ANN are the link traversal time predictions that the Vehicle Agents need to plan their routes.

The use of ANNs has a number of benefits:

- The relationship between the intention levels and the link traversal times can be treated as a *black box*.
- The ANNs are *flexible*. They allow a varying number of *inputs*.
- Evaluating an ANN is *fast*. Training the network is a slow process, but can be done without keeping other agents waiting.
- Robust *implementations* of ANNs are available.

The use of ANNs limits the effort to model a road to the choice of the number of inputs n and the δ parameter. No other parameterization is required. The specifics of the road are learned online.

The online learning has other benefits as well. The bias to compensate for partial participation is updated while the system operates. As long as there are no sudden changes in the participation rates, the ANNs can update their bias to compensate.

The evaluation of the ANN based approach in Chapter 6 is based on simulations of a couple of hours. When using the ANNs to make predictions in scenarios that have a longer duration, different training approaches may be required.

Chapter 5

Experiment Setup

Evaluating large scale advanced traveller information systems (ATISs) is a major challenge. Because of the scale and complexity it is nearly impossible to do real world tests. Instead, the evaluation is usually done *in silico*, via computer simulation. Traffic simulation software allows the modeling of the state of a traffic network and its users and the simulation of the evolution of state over time.

The results of the evaluation depend not only on how realistic the traffic simulation is. It also depends on the realism of the simulated scenario. Evaluating a coordination mechanism in a highly unrealistic scenario will give little information on how the coordination mechanism will behave in the real world.

To assess whether the AntTIS system meets the requirements of being able to guide a large population of vehicles in a large-scale traffic network we need a scenario that has a sufficiently large traffic and complex traffic network and that has a sufficiently large population to coordinate. The interactions between the different agents described in Chapter 3 and the prediction process described in Chapter 4 will serve as test to see whether the delegate multiagent system (dMAS) based approach is applicable in the traffic domain.

For this purpose, the main requirements of the evaluation are large traffic networks with a complexity that is similar to real-world traffic networks and a population of vehicles that is of roughly the same size as the population that would otherwise make use of the traffic network used in the evaluation. The combination of these will require communication, information exchange and interactions of the same scale the system would face in a real-world deployment.

A good experiment requires scientific control. In the experiments described in this thesis the focus lies on how good AntTIS performs in a number of scenarios. In order to evaluate hypotheses about this we need to clarify two things: how are we to measure “performance” and what qualifies as “good”. In order to quantify the performance of route guidance systems we have defined a number of metrics that quantify the quality of the overall route choice. We have setup a base-line, a number of simulations in which AntTIS was not used to guide traffic, in order to allow comparisons.

To facilitate the simulation based evaluation of the AntTIS system, a microscopic traffic simulator called GridLock was developed [21]. The design and rationale behind this simulation framework is also discussed in this section.

Overview This chapter discusses the evaluation process and the setup of the experiments described in Chapter 6. Firstly Section 5.1 introduces the hypotheses that will be validated. Section 5.2 describes the metrics used to quantify the quality of the route choice in a scenario. Section 5.3 describes the traffic simulation software and the traffic simulation model used in the experiments. Next, Section 5.4 describes the different traffic scenarios used in the experiments. Finaly, Section 5.5 discusses some caveats regarding the evaluation setup.

5.1 Hypotheses

The starting point for the evaluation of the AntTIS system is a number of hypotheses. These hypotheses capture the assumptions made about the AntTIS system. This chapter describes the experiment setup later used to evaluate these hypotheses in Chapter 6.

5.1.1 Intention Propagation is able to predict traffic conditions

The ATIS described in this thesis relies on the prediction of link traversal times, the time it takes a vehicle to traverse a certain link in the traffic network while subject to the traffic conditions on that link. These predictions play a crucial part in deciding which route to choose.

Our approach does not assume total participation. Not every driver will be guided by the ATIS we propose, and not every driver will contribute information to the system. Even without full participation, the system should still be able to make meaningful predictions of future link traversal times.

Hypothesis 1. Given sufficient participants sharing their intentions, the anticipatory vehicle routing system can accurately predict the traffic conditions during the time interval of the participants' trips.

5.1.2 Anticipatory vehicle routing leads to a user optimal route assignment

The system described in this thesis does not exert any external influence on the drivers that participate. It does not offer rewards to drivers following its advice, nor does it penalize drivers that do not comply with the advice given. The only incentive the system offers the drivers is the quality of the advised route.

One consequence of this limitation is that the resulting route assignment will be user optimum. Users of the system still selfishly choose routes that benefit themselves. The route guidance system cannot force the traffic towards a system optimal state, as that would require external incentives.

The route assignment observed in real world traffic is also user optimum [97]. Drivers base their route choice on their knowledge of previous choices. When a driver has the option to select a better route, he or she will choose the better route regardless of the consequences that choice will have on other road users.

Hypothesis 2. The quality of the routes advised by the anticipatory route guidance system matches the quality of the routes in a user optimal route assignment.

5.1.3 Anticipatory vehicle routing benefits perturbated traffic networks

Real-world day to day traffic operates under a user equilibrium. Under this equilibrium, no driver knows of a route that would result in a shorter travel time or he would switch to that alternative route.

This equilibrium is reached through the historical observations made by drivers of the traffic conditions they encounter. If, because of some perturbation, the traffic conditions change then the equilibrium will no longer be user optimal.

However, since the drivers have no historical knowledge of the perturbated traffic conditions, they are unable to change their route choice.

The ATIS described in this thesis will help drivers facing an unknown network in making good routing decisions. Drivers following the route guidance in such a situation will have routes of better quality than if they choose based on their incorrect historical knowledge.

Hypothesis 3. Given a traffic network in which demand or supply is altered, the route quality of routes advised by the anticipatory route guidance system is better than that of drivers depending on their knowledge of the original traffic networks response to the original travel demand [45].

5.1.4 Anticipatory vehicle routing does not require complete participation

A situation in which every driver participates in the route guidance system described here is unrealistic. Therefore, the system must be able to cope with partial participation. Even under such conditions should the route guidance system offer meaningful route guidance to drivers participating in the system.

Hypothesis 4. The three previous hypotheses hold even when not all traffic participates. Not every driver has to share his intention with the system and follow the systems advice. There is however a critical threshold that must be met in order for the system to function properly.

5.2 Evaluation Criteria

Evaluating the quality of a route guidance system is very difficult. To learn how a route guidance system would perform when deployed, the evaluation should be as realistic as possible. This requires a realistic and large scale scenario. The routes assigned to individual drivers in the simulation of such a scenario should be evaluated using metrics that give an indication of the quality and fairness of the routes. Such an evaluation is difficult because it is hard to define the "quality" and "fairness" of a set of routes. When dealing with thousands of vehicles, the amount of data needed to make the analysis becomes an obstacle as well.

In this thesis we assess the quality of a route assignment by looking at the quality of the individual routes. We determine the quality of a route based on its length and the time it takes the vehicle to reach its destination when following that route. The time it takes the vehicle to reach its destination takes into account the effects of traffic and is the result of the simulations described in Section 5.3.

In order to assess the quality of routes in a given experiment we have defined the following criteria.

1. **Trip distance** The total distance travelled by a vehicle while travelling from its origin to its destination.
2. **Trip duration** The total time spent driving by a vehicle travelling from its origin to its destination.

Simply measuring these trip attributes does not lead to a meaningful evaluation. The trip attribute data has to be compared with other data of similar trips in order to assess the quality of the routes assigned by the route guidance system. In this thesis, the data is compared in two different ways:

1. **Comparison with a base-line.** We compare the trip distance and duration of a vehicle in an experiment with distance and duration of the trip that same vehicle makes in the base-line simulation. In the base-line simulation no coordination is performed. The metrics based on the base-line case will have a b superscript. More details on how this base-line was determined can be found in Section 5.2.1.

   All the metrics used in the evaluation are relative metrics. Trips, even within one scenario, can differ greatly in both duration and distance. A comparison of two trips in the Highway scenario (Section 5.4.2) where one traverses the whole of Flanders while the other is very short is almost impossible without using relative metrics. The relative nature of the metrics do cause smaller trips to have a bigger impact on the end results.

2. **Comparison among peer pairs.** We compare the trip length and duration with the trip length and duration of other vehicles with similar origins, destinations and departure times. The metrics based on similar peers have a p superscript.

   Details on how the vehicles with similar origin and destinations where chosen can be found in Section 5.2.2.

Together these two methods of comparison provide us with a view on how the trip quality is affected by introducing an ATIS. The first metric gives the quality of the trips relative to a base-line. Thus showing the overall influence of the ATIS. The second metric gives an indication of the quality of the trips relative to other trips within that experiment. This is an indication of the fairness of the ATIS.

An ATIS that leads to bad results according to the second metric will most likely be evaluated poorly by its users. A large portion of its users will notice that other users with comparable origin and destination pairs receive far more favourable trip advice. This gives a sentiment of injustice.

For both types of metrics, base-line and peer based, we devise metrics quantifying both the duration and length of the trips. Metrics dealing with duration will have a d subscript while metrics dealing with length will have a l subscript. In the remainder of this section d will symbolize a duration while l will symbolize a distance.

A simple metric to evaluate the quality of a route assignment does not exists. Metrics that aggregate all results ignore the fairness of the solution and favor assignments in which only few drivers benefit from the coordination.

By comparing with both the baseline and the set of peers, the metrics introduced here assess both the quality and fairness of the proposed coordination mechanism.

5.2.1 Comparison with the base-line

To assess the impact of an ATIS we compare the duration and distance of a trip with the duration and distance of that same trip in the base-line. The base-line with which the ATIS will be compared is an approximation of a user equilibrium under user optimal conditions.

Under the user optimum, no vehicle can choose an alternative route that would result in a shorter trip duration. This resembles the state of actual day to day commuting traffic. Vehicle drivers that learn of a route that would result in shorter commuting times are likely to switch to the alternative route. When no driver knows of a better route, the switching stops and an equilibrium is reached [97].

Both the quality of the trip duration and the trip distance are quantified.

$$q_l^b(t_i) = \frac{l_i^b}{l_i} \tag{5.1}$$

Where q_l^b is the metric describing the length of trip t_i in an experiment; l_i^b and l_i are the lengths of t_i in respectively the base-line simulation and the experiments simulation.

A q_l^b score of 1 means that the length of the trip in the experiment was similar to that in the base-line. A q_l^b score > 1 means that the length of the trip in the experiment was shorter than the length in the base-line.

The quality of the duration of trip t_i is described by:

$$q_d^b(t_i) = \frac{d_i^b}{d_i} \tag{5.2}$$

.

Where d_i^b is trip t_i's duration in the base-line simulation and d_i is trip t_i's duration in the experiment simulation.

A q_d^b score of 1 means that the duration of the trip in the experiment was similar to that in the base-line. A q_d^b score > 1 means that the duration of the trip in the experiment was less than the duration in the base-line.

Determining the base-line

To assess the quality of an ATIS a baseline result with which to compare its performance is needed. This section describes how we determine that base-line by approximating a user equilibrium under user optimality. We can only approximate the user equilibrium as calculating it for a microscopic traffic assignment is not feasible.

Given a traffic scenario with a certain origin destination matrix, the base-line simulation is a simulation of the exact same destination matrix. The routes for all trips in the origin destination matrix are determined through an iterative process.

Below, a description of the process is followed by an example of how it is applied. This iterative process is known as *incremental assignment*. The different steps in the process are

1. The overall origin destination matrix is randomly divided into a series of n fractions, P_i with i going from 1 to n. These fractions grow ever smaller. A division could be: 50%, 25%, 15%, 5%, 5%.
2. A sequence of simulations S_j with j going from 1 to n is started. Every simulation S_j involves fractions P_i with i going from 1 to j.

3. In simulation S_j, the routes determined in the previous step, S_{j-1} for P_i with i ranging from 1 to $j-1$ are kept fixed.

4. In simulation S_j the routes for fraction P_j are calculated based on the travel times observed in the traffic network for S_{j-1}

5. After all fractions have been simulated in S_n, every trip in the origin destination matrix has been simulated.

The route assignment described above is not optimal. As the route assignment for fraction P_i is based on all previous simulations, the route assignment of P_i assumes that vehicles in P_j with j ranging from 1 to $i-1$ will influence P_i. It also assumes that the vehicles in P_i do not influence each other. The fraction size has to decrease in order for this assumption to hold.

Example walk through. Given fraction sizes 50%, 25%, 15%, 5% and 5%, and an origin destination matrix consisting of 100 trips each with an origin, destination and departure time.

The origin destination matrix is randomly divided into the five fractions. First 50 trips are selected at random and are placed into P_1. Next, from the remaining 50 trips, 25 trips are selected and placed into P_2. This continues with 15 trips for P_3, 5 trips for P_4 and the last 5 trips for P_5.

A route selection algorithm such as A^* is used to calculate the routes for P_1 based on the static information present in the traffic network. Static information on both speed limits, link lengths and link capacity is used to make link travel time estimates for all roads in the network. These link travel time estimates are used in the route calculation algorithm. The route assignment is simulated in S_1. Simulation S_1 thus only includes the trips from P_1. During S_1 the link traversal times for all links in the network are recorded as a function over time.

Prior to the next simulation, S_2, the routes for P_2 are calculated using a time dependent routing algorithm [30] based on the link travel times measured during S_1. In simulation S_2 the routes of P_1 together with the newly calculated routes for P_2 are simulated. Again, the link travel times for all the links in the network is recorded as a function over time.

This process continues until the routes of all trips in all fractions are calculated. This occurs just before running simulation S_5. The outcome of that simulation, the route distance and duration for all trips, is the base-line.

5.2.2 Comparison among peers

To assess the fairness of the routes advised by an ATIS we compare the routes calculated for trips that have both similar origins, destinations and departure times. If there are large discrepancies between the routes calculated for similar trips, this will result in a feeling of injustice and unfairness with the users of the ATIS.

In order to calculate this metric, we first divide the trips into sets of similar trips (Section 5.2.2). Given such a set of trips T_i we determine the minimal trip duration d^i_{min} and minimal trip length l^i_{min} for that set. Based on these minima, we define the following metrics:

$$q^p_d(t_j) = \frac{d^i_{min}}{d_j} \mid t_j \in T_i \tag{5.3}$$

$$q^p_l(t_j) = \frac{l^i_{min}}{l_j} \mid t_j \in T_i \tag{5.4}$$

Here q^p_d quantifies the quality of the trips duration among its peers and q^p_l quantifies the quality of the trips length among its peers. d_j and l_j reference respectively the duration and length of trip t_j.

Similarly to the base-line based metrics higher values indicate higher qualities. With the peer based metrics the maximum score is 1. Trips scoring 1 are the trips with l^i_{min} or d^i_{min} values.

Determining sets of similar trips

To compare the quality of a trip within a set of similar peers we need to divide all trips into a number of sets with similar features. The features used to determine similarity are: the origin, the destination and the departure time of a trip.

These features are all based on the origin destination matrix (Section 5.4). This matrix is fixed throughout different experiments. The division of trips into sets can be reused as long as the origin destination matrix remains identical. This allows for comparison across different experiments with the same origin destination matrix.

All three features are necessary for the division. Discarding the influence of one would bias the resulting comparison. Two vehicles leaving at the same origin for the same destination at different times would encounter different traffic situations. Two vehicles not having a similar origin and destination are likely forced to use different parts of the traffic network.

The division of trips into distinct sets is done by applying a K means clustering algorithm on an origin destination matrix (Figure 5.1-5.4). First, the trips are clustered based on their origin destination pairs. Here the clustering is based on euclidean distance. Then, for each cluster with similar origins and destinations, the results are clustered based on their departure time.

The K means clustering algorithm provides us with a simple mechanism to group similar trips in sets. By clustering both on the position of the origin and destination and on the time of departure, the clustering process ensures that the trips in one set are similar in both spatial and temporal aspects. The vehicles making the trips in one set are thus very likely to encounter similar traffic conditions.

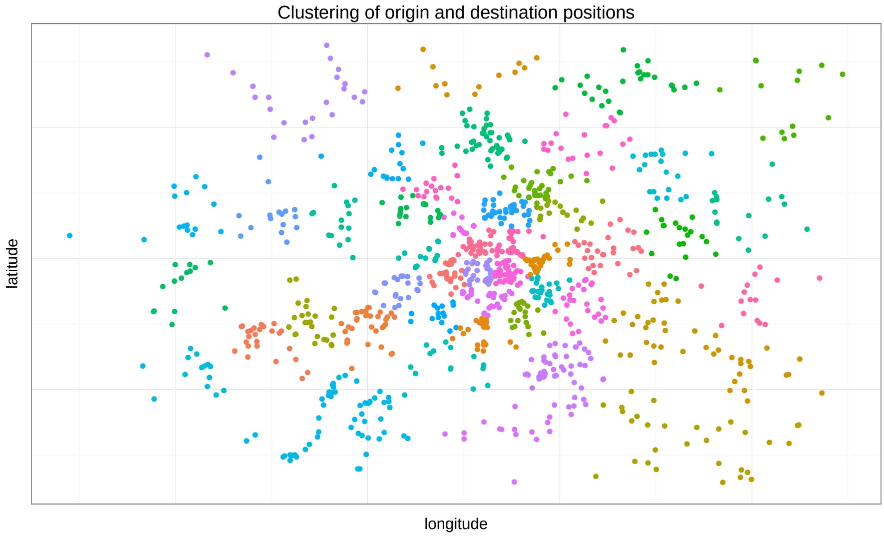
The K means clustering algorithm only takes one parameter: the number of clusters that are to be calculated. Finding the right number of clusters is a challenge. If there are too few clusters, trips that do not share any similarity will be compared. If there are too many clusters, there will be sets that only contain one or two trips. Those sets invalidate the results. In a set containing only one trip, all trips are optimal.

The number of clusters is determined iteratively by hand. We start with a large number of clusters and gradually reduce the number of clusters until (1) there are no more singletons and (2) the similarity within a cluster is still sufficient given the size of the scenario. An automated way of determining the number of clusters does not exist. However, by looking at the cluster sizes, a suitable number of clusters can be found by experimentation.

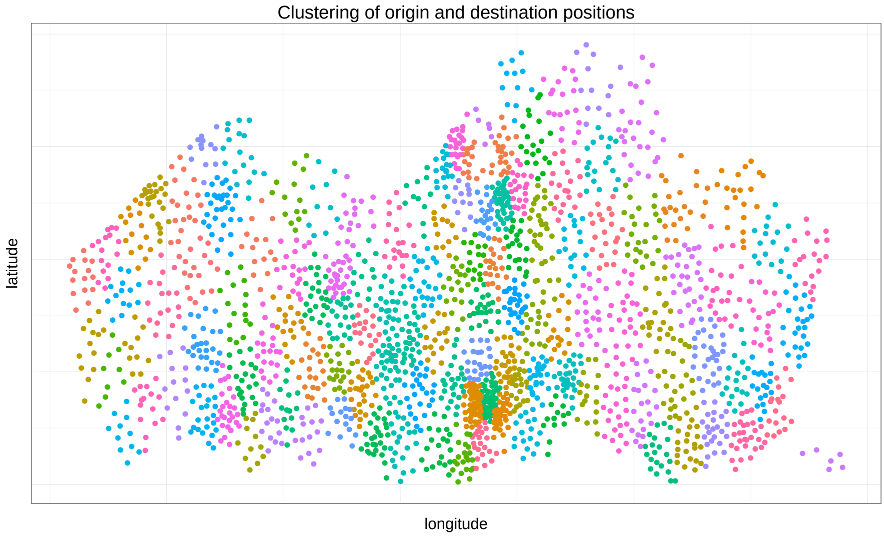
An example clustering is shown in Figures 5.1-5.4. Figure 5.1 shows the clustering of the origin and destination positions. Figure 5.2 shows the size in terms of origin and destination positions and the geographical center of the clusters. Figure 5.3 shows how the cluster size in terms of position is distributed and Figure 5.4 shows how the cluster size in terms of vehicles in distributed.

5.3 Microscopic Traffic Simulation

All experiments conducted to evaluate the performance of AntTIS are simulation based. This section describes the simulation model (Section 5.3.1) and the simulation software (Section 5.3.2) used to conduct the simulation experiments. While the software [21] is developed specifically for the experiments described

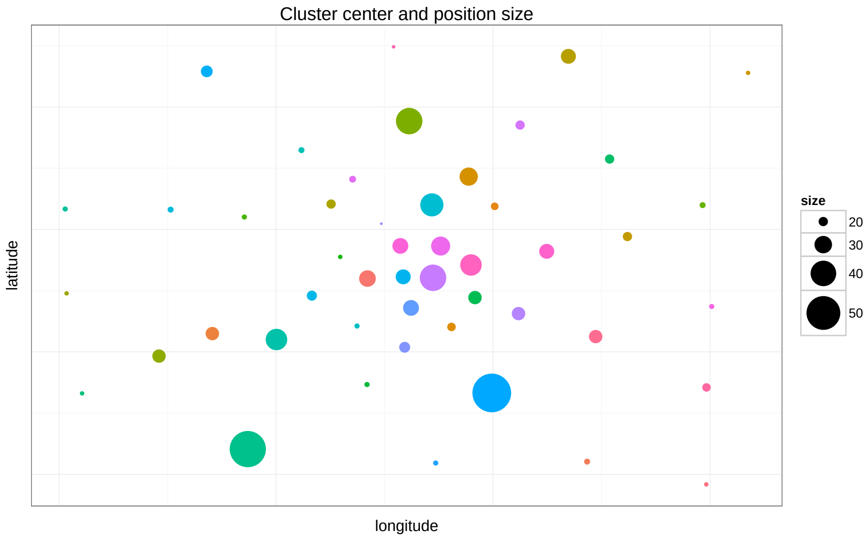


(a) Clusters for Leuven

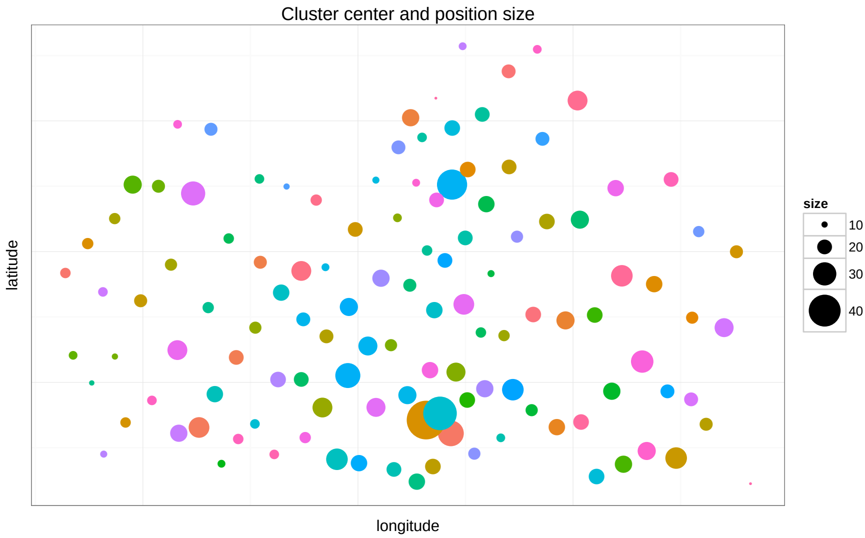


(b) Clusters for Flanders

Figure 5.1: Clustering of origin and destination locations. The different colours indicate the cluster the location was assigned into. Trips are divided into sets based on both the cluster of their origin as the cluster of their destination.

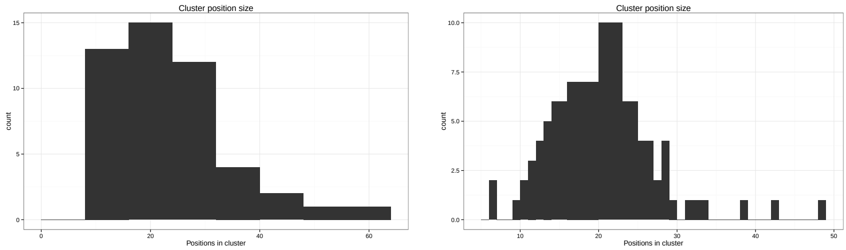


(a) Cluster sizes in Leuven



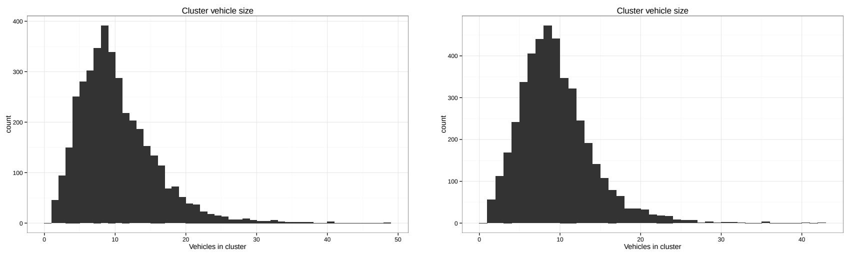
(b) Cluster sizes in Flanders

Figure 5.2: Size of the various clusters. The number of clusters is the only parameter used in the K means algorithm. Choosing a good value is important as small clusters will give biased results.



(a) Cluster sizes in Leuven (b) Cluster sizes in Flanders

Figure 5.3: Histogram showing the distribution of the cluster sizes (in terms of origin and destination points) for both the Leuven and the Highway scenario.



(a) Cluster sizes in Leuven (b) Cluster sizes in Flanders

Figure 5.4: Histogram showing the distribution of the cluster sizes (in terms of vehicles) for both the Leuven and the Highway scenario.

in this thesis, the traffic model implemented in the simulation is taken from literature [14].

5.3.1 Queue Based Microscopic Traffic Model

The traffic model described by Cetin et al. in [14] is a *microscopic* traffic model. Instead of describing traffic in terms of traffic flows, microscopic traffic models model every individual vehicle on the road. This hinders their scalability, but is a necessity for most multiagent systems (MASs) research. Most multiagent traffic guidance systems assign an agent to guide every individual vehicle. In order to evaluate such systems, it is essential that these individual vehicles are explicitly modelled during the simulation process.

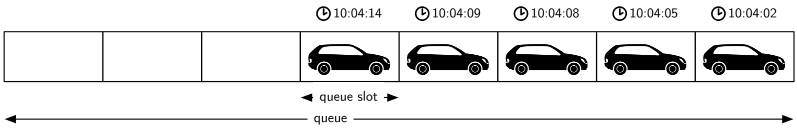


Figure 5.5: Roads are represented as queues in the simulation model. Every queue has a number of slots corresponding to the length of the road. Vehicles entering the road are added to the back of the queue. The order of the vehicles and the time they can leave the road make up the state representation of the road.

Queue Based Simulation of Roads

To improve the scalability of the microscopic traffic model, Cetin et al. sacrifice some level of detail in their model. In stead of keeping track of the position of every vehicle on every road, the model keeps track of the order in which the vehicles enter and the time earliest time they would be able to exit the road. Every road is thus modelled as a queue. Upon entering a road, a vehicle is placed at the end of the queue. For every vehicle in the queue, the model calculates how long it would take the vehicle to traverse the road if it were to drive at maximum speed without other vehicles hampering its progress. This is the only information describing the state of a road: a queue of vehicles each with their earliest departure time (Figure 5.5).

Traffic network constraints are enforced at two locations. The constraint imposed by the limited space capacity of a road is enforced at the start of the road. When a vehicle wants to enter a road and is at the head of a preceding road, the vehicle is only admitted to the road if there is a slot available in the queue. The number of slots in the queue is calculated based on the average vehicle length, the length of the road and the number of lanes in the road. The constraint imposed by the limited throughput of a road is enforced at the end of the road. During the state transition, when the next state of the road is calculated, the number of vehicles exiting the road is counted. If this number exceeds the throughput capacity, the vehicle is not allowed to exit. When a vehicle at the head of the queue is ready to leave, i.e. its departure time is less than or equal to the current virtual time, it can be held back because of these two reasons. The throughput of the road it is currently on would be exceeded or the space available at the road it is to enter would be exceeded. Vehicles unable to leave the road because of any of these constraints remain at the head of the queue, preventing vehicles behind it to exit the road even though those vehicles' departure times might have been reached. Because of this mechanism, congestion can form.

The simulation described in the work of Cetin et al. is event based. It only calculates the next state of the traffic network when an event that causes a state change is expected. This allows the simulation software to jump forward through the virtual time. This event-driven approach improves the scalability of the simulation, but it is often difficult to also use the event-driven approach to drive a MAS.

Event-driven simulations only calculate the model state when an event occurs. In between events, the model's state is left implicit. Agents operating in a MAS often make proactive decisions and have an ongoing reasoning cycle. In a purely event-driven system, agents are only able to observe their environment when the model representing that environment is explicitly calculated. Thus, they can only observe their environment when an event occurs. This hinders their ability to make proactive decisions.

In the implementation used in this thesis, the queue-based simulation model is evaluated using a time-frame based simulation. The simulation software increases the virtual time with a small and fixed increment and calculates the new state of the model at that new virtual time. Given that the time increment in the time-frame based simulation is small enough, the outcome is identical to the outcome of the event-driven approach.

Queue Based Simulation of Intersections

Intersections are also modelled as queues. An intersection can hold a limited number of vehicles. Vehicles are only allowed to exit the intersection queue if the road the vehicle chooses has a free slot at the entry. Vehicles unable to exit the intersection will remain in the queue, preventing other vehicles from entering the intersection. This results in the congestion spilling over from one link to the adjacent links.

More complex intersection layouts are not supported. Intersections where cars have to enter through certain lanes in order to choose an exit road, for example, are not supported due to both the simple road and intersection modelling. However, intersections where certain incoming and outgoing roads are directly connected can be modelled by explicitly adding the connection as a separate road bypassing the intersection. The same holds for roundabouts, they are modelled as circular roads connecting all roads leading to the roundabout.

Because little information on intersection capacity is available, the capacity is automatically calculated if no capacity is provided. The default capacity of an intersection is the maximum outgoing capacity of all roads leading to the intersection. This ensures that not the capacity of the intersection, but the outflow capacity of the roads limit the throughput of the roads.

Priority rules are enforced by the simulation model. Based on the type of priority rules at the intersection, the intersection will only allow vehicles to enter from one road. If the type of priority for an intersection is not specified, it is assigned automatically. On intersections that connect roads of different classifications, for example a residential street connecting to a main road, the highest classification is given priority. Intersections connecting roads of the same classification will use a give way to the right model.

5.3.2 GridLock Simulation Software

This section describes the software system used to perform the simulations. The coordination system described in this thesis is evaluated using simulation software developed specifically for evaluating multiagent based traffic coordination mechanisms.

Interaction Between Agents and Traffic

The GridLock simulation software is mainly targeted at evaluating multiagent based coordination mechanism. The interaction between the simulated environment and the agents is important.

In GridLock this interaction is as asynchronous as possible. All information about entities such as vehicles or an infrastructure (road or a crossroad) is accessible to the agent assigned to that entity. To control a vehicles' movements, the agent informs the vehicle of which path to follow. The microscopic traffic simulation will then adhere to these instructions. Vehicles without valid paths will raise errors.

The path a vehicle needs to follow is thus embedded in the simulation system. The simulation thus does not need to call upon the coordination module whenever a driving decision needs to be made. Agents can override their vehicles path whenever they change their mind on which route to follow. The change of route will take effect immediately.

The low level driving operations (acceleration, braking, lane changing) is taken care of by the microscopic simulation model and the driver model used in the simulation. These low level behaviours can not be influenced by the agent, as they are part of the scenario and not the coordination mechanism.

Event Based Instrumentation

The main goal of the GridLock simulation software is to evaluate large-scale traffic coordination mechanisms. The instrumentation of the simulation is therefor very important.

A thorough analysis of an experiment requires information about various facets of the simulated environment. We need information concerning both the simulated traffic environment and how the coordination mechanism performs. As GridLock is designed as an extendible and modular system, tying all modules into the instrumentation is not trivial.

Because of these concerns, all instrumentation within GridLock is event based. Various modules in the system can emit events before, during and after the simulation. All information needed to do the analysis afterwards has to be included in the events.

The events emitted during a simulation can be stored in a database for off-line analysis, but they can also be analyzed during the simulation. This allows for some aggregation and filtering of the information.

Traffic Network Data

The simulation software can handle traffic network definitions from various sources. The main two sources used as basis for the scenarios described in Section 5.4 are XML descriptions of OpenStreetMap[1] information and Esri shapefiles containing traffic network information provided by the Flemish Center for Traffic (Verkeerscentrum Vlaanderen).

The road and intersection attributes provided by both sources differ. For example, the shapefiles contain information about road capacity, the OpenStreetMap data does not. In cases where crucial information is lacking, it is derived from other attributes that are present. The capacity for example is derived from the road classification, the free-flow speed limit and the number of lanes.

5.4 Traffic Scenarios

To evaluate the anticipatory vehicle route guidance described in this thesis two traffic scenarios were developed. A complete traffic scenario consists of two

[1] http://openstreetmap.org

parts: an annotated traffic network graph and the description of traffic that makes use of the network.

The annotated traffic network graph describes the roads available in the network. Every road is annotated with information needed to simulate traffic on that road. Information needed to simulate traffic includes the speed limit, the number of lanes and the capacity of the road.

A description of the traffic network is only part of the scenario. The scenario must also include a description of the traffic. The complete traffic usage in a scenario is described as a list of quadruples. Every quadruplet describes a single trip taken by a single vehicle on the traffic network. The quadruples contain:

1. the time at which the trip starts
2. a unique identifier for the trip
3. the trip origin
4. the trip destination

This list is used by the simulator to generate traffic during the simulation. At every time step the simulator selects the trips that should start. For every starting trip the simulator inserts a vehicle at the trip's origin. That vehicle will then drive towards the trip's destination. The vehicle is labelled using the trip's unique identifier. The unique identifier thus allows us to compare how a certain trip was performed in various simulations.

The list of quadruplets describing the traffic demand allows us to reproduce certain traffic situations throughout a number of different experiments.

This section describes the two basic scenarios used in the evaluation of the AntTIS route guidance system. The first scenario is an urban scenario and describes traffic in and around the city of Leuven. The second scenario is larger, but less detailed, and describes the network of highways in Belgium.

5.4.1 The Leuven Scenario

This scenario centers around the city of Leuven. It combines a very detailed traffic network with realistic urban traffic patterns. Both the traffic network and the trips in the traffic description are based on real-world observations. Although the scenario was not designed and calibrated for the use in micro-simulation, the network is a network with a realistic layout and size, and the number of trips represent a realistic traffic load for a network of this size.

Figure 5.6: Traffic network used in the Leuven scenario.

Traffic Network

The network used in this scenario is based on data obtained from the Flemish Center for Traffic[2]. The network describes the surroundings of the city of Leuven (Figure 5.6). More details about the network can be found in Table 5.1.

Traffic Description

The description of the traffic loaded into the Leuven traffic network is based on data obtained from the Flemish Center for Traffic. The scenario describes the traffic during one hour between 8:00 and 9:00. More details on the traffic can be found in Table 5.1. Figures 5.7-5.9 show various attributes of the origin destination matrix used.

[2] Het Vlaams Verkeerscentrum

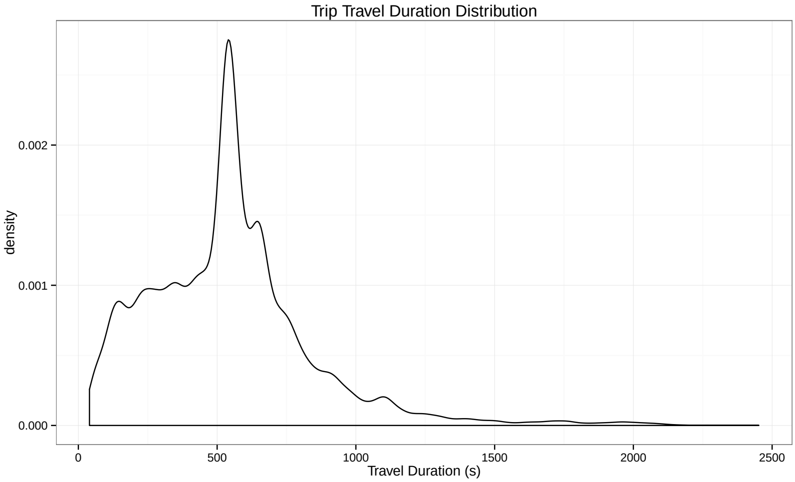


Figure 5.7: The distribution of the trip duration for the Leuven scenario in the base-line simulation.

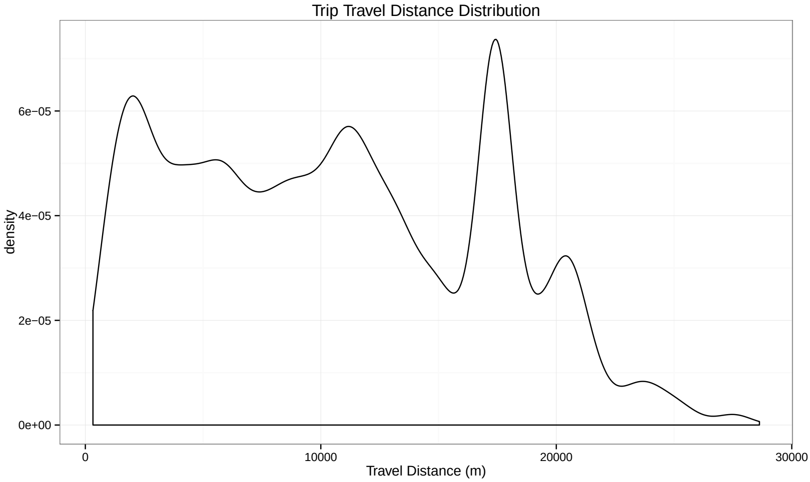


Figure 5.8: The distribution of the trip distance for the Leuven scenario in the base-line simulation.

Number of Vehicles	37598
Number of links	2662
Total link length	1068 km

Table 5.1: Traffic characteristics of the Leuven scenario.

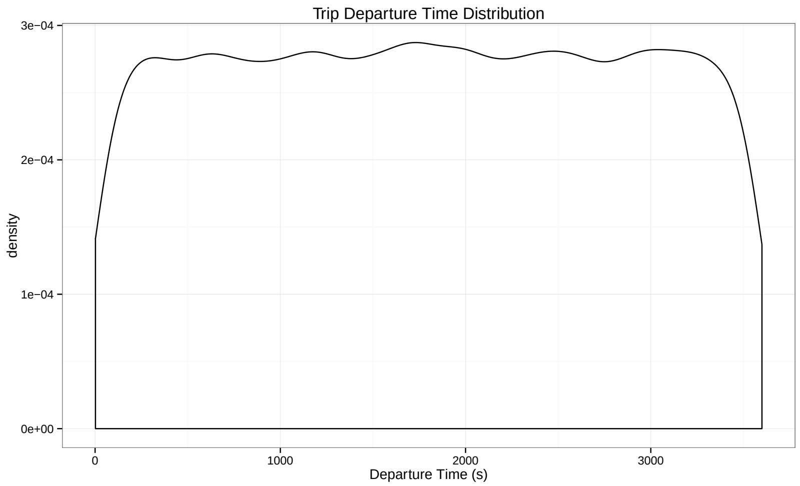


Figure 5.9: The distribution of the trip duration for the Leuven scenario in the base-line simulation The values on the x-axis indicate the time of departure relative to the start of the simulation.

5.4.2 The Highway Scenario

This scenario centers around the highway network in Belgium. The traffic network includes only major roads. The network in this scenario is based on a crowd based network description. The network might contain inaccuracies due to the unofficial and collaborative nature of its origin, it is still a network of a realistic size and complexity. The trips in this scenario are not based on real-world measurements or observations. They are based on an activity based model that is based on real-world observations and surveys.

Number of Vehicles	489323
Number of links	80471
Total link length	77536 km

Table 5.2: Traffic characteristics of the Highway scenario.

Traffic Network

The road network used in this scenario is based on data that is freely available in OpenStreetMap. Only roads with a classification of `primary` and higher[3] in the OpenStreetMap highway classification are included. More details about the traffic network in this scenario can be found in Table 5.2.

Traffic Description

The origin destination matrix used in this scenario is based on an activity based model. The model predicts the traffic demand between statistical sectors. The traffic intensity between two sectors is influenced by the demand for activity in the originating sector and the supply of the destination sector [11]. Details on the origin destination matrix can be found in Table 5.2.

5.5 Evaluation Caveats

Throughout this chapter the difficulty of evaluating large scale route guidance systems has been mentioned. This section describes some of the issues that have not been overcome in setting up a fair and unbiased evaluation.

5.5.1 The realism of the simulation model

The microscopic model used in the traffic simulation is a very basic queue based model (Section 5.3.1). This queue based model omits many details of a traffic network. The most important details omitted from the model are:

- Very limited modelling of intersections.
- Queues are first in first out. Overtaking is not modelled.

[3] `trunk` and `motorway`

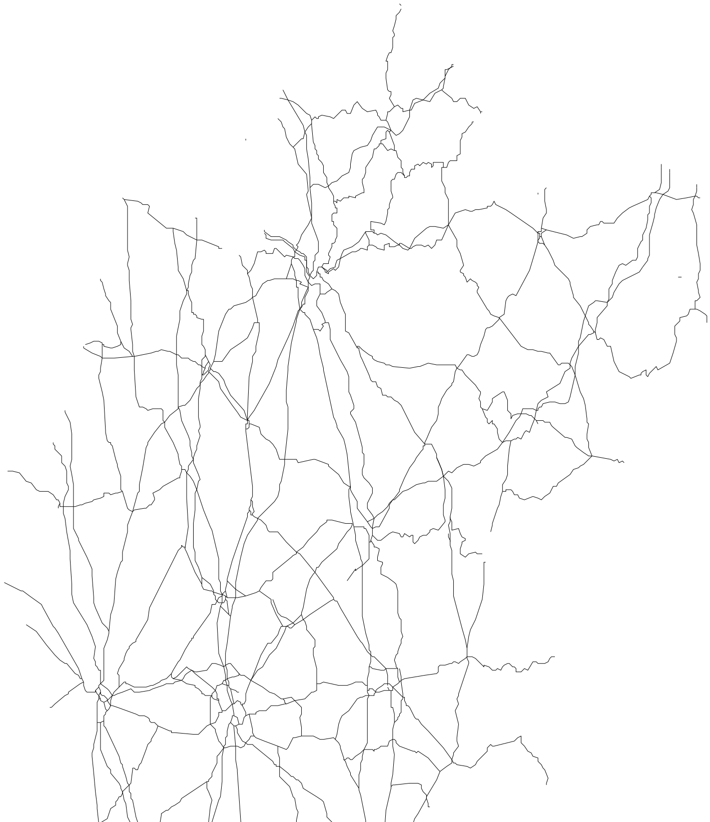


Figure 5.10: Traffic network used in the Highway scenario.

- Vehicle interactions are not modelled.

Despite these limitations, we feel that the queue based model is still a suitable microscopic model for evaluating a large-scale coordination mechanism because the omitted details have a limited effect on the overall quality of the trips, because both the coordinated and the uncoordinated trips in the base-line case are modelled using the same model and because the queue based model simple representation allows us to conduct experiments at a larger scale than more detailed representation would allow.

Together, these three reasons justify the use of the queue based microscopic model.

The model does not take into account the complexity of crossroads and intersections. Nor does it model inter-vehicle interactions that lead to traffic slowdown when traffic intensity increases. This is likely to make the traffic patterns observed in the simulation easier to predict. Thus influencing the evaluation made in Section 6.2.4 in our advantage.

5.5.2 The realism of the scenarios

The degree of realism in the scenarios is determined by three factors:

1. The realism of the traffic demand description.
2. The realism of the traffic network description.
3. The realism of the simulation model used.

The realism of the simulation model is already discussed in Section 5.5.1. This section discusses the first two factors.

Realism of the traffic demand. In both the Leuven and the Belgian Highway scenario the traffic demand information is based on real-world observations. The origin-destination matrix that serves as input for these scenarios is, in both cases, macroscopic.

A macroscopic origin-destination matrix describes the traffic flow between regions in the traffic network. It states that *in interval x, y vehicles will travel from region a to region b.* The information here is aggregated both in the time and the space domain. In order to use such a macroscopic origin-destination matrix as the input for a reproducible microscopic simulation, the matrix must be disaggregated.

The disaggregation occurs in two steps. First for every of the y vehicles, a departure time t is chosen uniformly in the time interval x. Then an origin is chosen from region a and a destination is chosen from region b. The result is a list of tuples as described in Section 5.4.

If the microscopic description of the origin-destination matrix would be aggregated with the same intervals and regions as the original macroscopic matrix, it would be identical to that input matrix. However, many microscopic origin-destination matrices can be generated from one macroscopic one.

To remove any bias that may be introduced in the disaggregation step we have generated 30 different microscopic origin-destination matrices for every macroscopic matrix that serves as input. All experiments are conducted on every one of these 30 matrices.

Realism of the traffic network. The traffic network in the Leuven scenario is based on information obtained from the Flemish Center for Traffic and is very detailed and realistic. The traffic network used in the Belgian Highway scenario is based on information extracted from OpenStreetMap. While there is a general consensus that the quality of the information found on OpenStreetMap is of very high quality [44, 61, 86], we cannot guarantee the accuracy of the information.

Despite possible mismatches between the traffic network described in OpenStreetMap and the real-world traffic network, the network described by OpenStreetMap can still be considered a realistic network.

Combining demand and network information from different sources. Both the description of the traffic demand and the traffic network in the Leuven scenario stem from the same source. In the Belgian Highway scenario, however, the source of the traffic demand and the traffic network information differs.

While both of the data sets are based on the real-world, together they might not be a real-world scenario. We believe, however, that while they might not be an actual real-world scenario, they still form a highly realistic scenario.

5.5.3 The quality of the base-line scenario

The equilibrium in the user optimal case is only an approximation of the user optimum. It is not guaranteed to be user optimal. Calculating the user optimum for the microscopic origin destination matrix is too complex.

It is however far better than a naive A* based solution.

Chapter 6

Experiment Results

This chapter describes the results obtained through the evaluation methodology, metrics and scenarios described in Chapter 5. Both the Leuven and the Highway scenario will be used in the following experiments:

1. **Undisturbed experiments.** In these experiments the scenarios are left unaltered.

2. **Disturbed experiments.** In these experiments we alter the scenarios after the baseline route assignment is established. The baseline route assignment is kept fixed and is evaluated in an altered scenario. We distinguish between two types of disturbances in the traffic network: flow disturbances and network disturbances. Flow disturbances are disturbances where the traffic demand is altered. We duplicate a part of the origin destination matrix to increase demand in traffic. Network disturbances are disturbances in the supply side of the network. Here the network definition is changed and the capacity of a number of links are severely reduced.

These experiments are performed for a number of participation rates. By varying the participation rate, the percentage of road users that participates with the AntTIS system, the impact of partial adoption of the system is evaluated.

When not all drivers participate with the AntTIS system, the non-participating drivers are completely excluded from the system. They are not considered dishonest or disobedient in the sense that they do not follow their intended route or give false information about their intended route. The non-participating drivers simply do not interact with the AntTIS system at all. They rely on the routes calculated for the baseline simulations instead.

For all experiments, the results will include an analysis of the predictions generated by the AntTIS system. Not all predictions handed out during a simulation are stored for later analysis. Due to the frequent querying of the Infrastructure Agents this would lead to an unmanageable amount of information. Rather, the predictions for some randomly chosen links are logged. These logs include the predictions throughout the simulation and for various time horizons.

Finally, this chapter will look back at the hypotheses first presented in Section 5.1. These hypotheses will be evaluated based on the results described in this chapter in Section 6.4.

Overview. This chapter starts by describing the design of the experiments more in depth in Section 6.1. Then the first results, those of the undisturbed experiments are discussed in Section 6.2. Next the disturbed experiments are described in Section 6.3. The chapter concludes with a discussion of all results and their consequences for the hypotheses in Section 6.4.

6.1 Experiment Design

The scenarios used in the experiments are based on macroscopic origin-destination (OD) matrices. The macroscopic OD matrices describe how many vehicles depart from one segment in the traffic network to another segment during a certain time interval. The macroscopic OD matrices do not describe individual vehicles.

For the microscopic simulation used in the evaluation, microscopic origin-destination matrices describing each individual vehicle are required. These microscopic origin destination matrix describe for every vehicle the point of origin, the destination point and the exact departure time. The step of going from the macroscopic level to the microscopic level is called the de-aggregation step.

The de-aggregation is non-deterministic. If one of the entries in the macroscopic matrix says that v vehicles will travel from origin zone z_o to destination zone z_d during interval t, then the de-aggregation step will generate v vehicles with a departure time taken uniformly from t. For everyone of these v vehicles, the de-aggregation step will randomly select a point of origin p_o from the set of points in z_o and a destination point p_d from the set of point in z_d.

Depending on the random seed used in the de-aggregation step, the microscopic origin-destination matrix might differ. To remove this bias, the de-aggregation step is repeated a number of times with different random seeds (Figure 6.1). In the experiments described in this section, the de-aggregation step is repeated 30 times, resulting in 30 unique microscopic origin-destination matrices. If one of these 30 microscopic origin-destination matrices where to be aggregated using the same zones and time intervals as in the original macroscopic origin-destination matrix, the result would be identical to the original macroscopic origin-destination matrix.

For every one of the 30 microscopic origin-destination pairs, we calculate the baseline solution based on the approach described in Section 5.2.1. This results in 30 result sets.

The baseline solution is only calculated once. When we evaluated the outcome of all 30 result sets based on the 30 microscopic origin-destination pairs we see very little variance. This indicates that the baseline calculation does not introduce a lot of variability and that repeating the calculation would unnecessarily complicate the process.

Every one of the 30 microscopic origin-destination pairs is also simulated using the AntTIS route guidance system. As AntTIS also involves non-deterministic elements, the simulations are also repeated for a number of times, each time with a different random seed. For the results in this chapter, the simulations where repeated 30 times. This results in $30 \times 30 = 900$ result sets.

The results shown in this chapter are, unless specified otherwise, the aggregated results of all these different scenarios and simulations. The first 10 minutes of the simulation is not included in the result set, unless specified otherwise, to account for network loading and initial artificial neural network (ANN) training.

6.2 Undisturbed Experiments

The experiments described in this section are the experiments labeled as undisturbed. This means that the traffic demand and traffic network used in the experiment are identical to the traffic demand and traffic network used to calculate the baseline route assignment.

Based on the simulation results the following analyses will be performed:

- **Analysis of the baseline simulation results.** By using the comparison amongst peers described in Section 5.2.2 we analyze the quality of the trips in the baseline simulation.

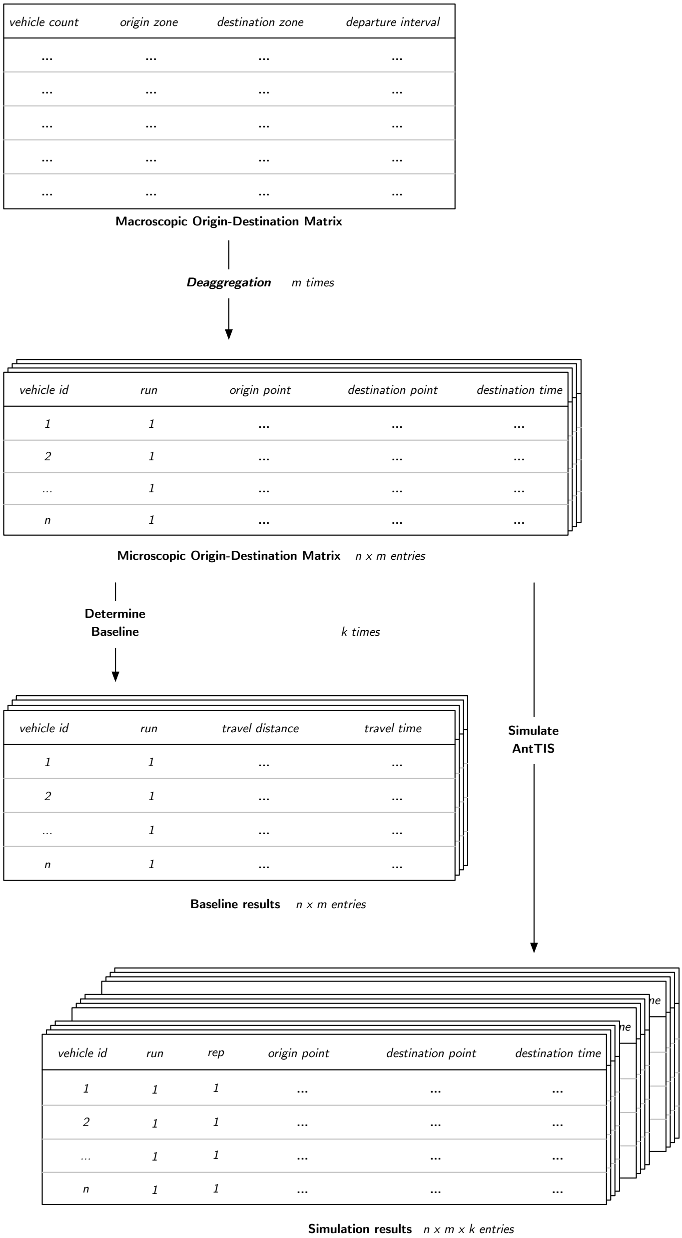


Figure 6.1: Design of the experiment. The scenarios are based on the macroscopic origin-destination (OD) matrices described in Section 5.4. Assuming the vehicle count columns in this matrix sums up to n, this matrix describes n vehicles. These macroscopic OD matrices are de-aggregated m times to remove any bias introduced in the de-aggregation process. For the m resulting microscopic OD matrices the baseline is determined. Everyone of the m matrices is also simulated k times using AntTIS. The end result are $n \times m$ trips over all baseline results and $n \times m \times k$ trips over all simulations using AntTIS.

- **Analysis of the AntTIS guided simulation.** The quality of the trips resulting from the AntTIS guided simulation is compared with the quality of the trips in the baseline scenario. The comparison is done both by comparing the travel time distribution and by using the baseline comparison metric described in Section 5.2.1.
- **Analysis of the impact of the de-aggregation.** By comparing the travel times and travel distances of all runs the impact of the de-aggregation is examined.
- **Analysis of the quality of the traffic predictions** By comparing the predicted link traversal times with the experienced traversal times, the quality of the predictions can be determined.
- **Analysis of the influence of the participation rate** The experiments in this section are repeated with a varying participation rate to assess impact of partial adoption on the quality of both the predictions generated by the AntTIS system and on the routes advised to the drivers.

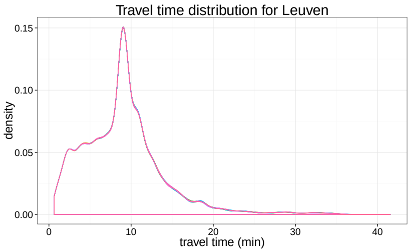
6.2.1 Analysis of the baseline

Analysis of the de-aggregation bias. To reduce the bias introduced in the de-aggregation step, all scenarios are duplicated 30 times by using different random seeds in the de-aggregation step (Section 6.1). Before analyzing the quality of the trips in the baseline simulation, the impact of the de-aggregation is studied.

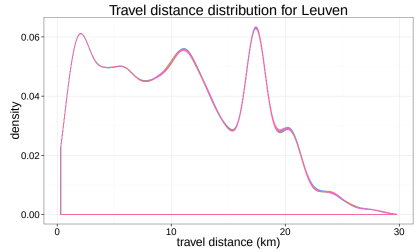
The distribution of travel times and travel distances for both the Leuven and the Highway scenario remain consistent over all different runs of the scenarios (Figure 6.2). The impact of the de-aggregation is therefore assumed to be minimal.

Analysis of the route quality. This section analyzes the quality of the routes that were assigned to the vehicles in the baseline scenario. The analysis is performed by looking at the distribution of both the travel time and travel distance and using the q_d^p and q_l^p metrics described in Section 5.2.2. As the analysis is performed on the trips in the baseline scenario, the metrics to compare with the baseline are useless. The metrics shown and discussed in this section are the result of averaging out over all the different de-aggregation runs.

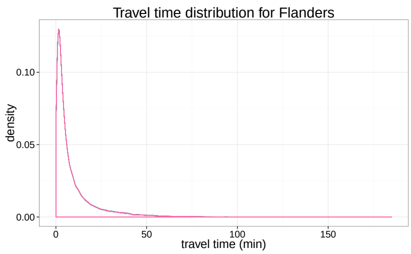
As described in Section 5.2.1 calculating the baseline is an iterative process. The baseline is assumed to be a user equilibrium that is reached when road



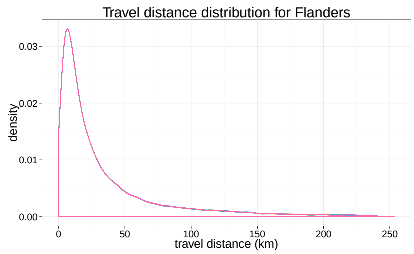
(a) Travel time for Leuven



(b) Travel distance for Leuven



(c) Travel time for Flanders



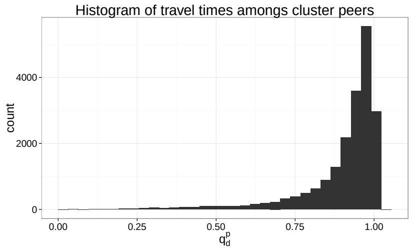
(d) Travel distance for Flanders

Figure 6.2: Distribution of travel time and distance in the undisturbed baseline simulation. The distributions for the different de-aggregated runs are plotted on top of each other. The distributions for both scenarios and both metrics are all very consistent, indicating that the bias introduced in the de-aggregation step is minimal.

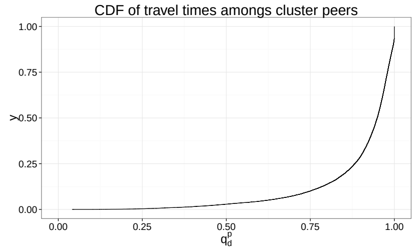
users know based on previous experience that they cannot choose a route with a lesser travel time than the route they intend to follow.

The distribution of the q_d^p scores in the baseline simulation (Figure 6.3) are concentrated at values very close to 1. This means that most vehicles in a cluster share the same travel time and that the vehicles decide that, based on all traffic state knowledge available to the vehicles in that cluster, they cannot improve their travel time by choosing another route.

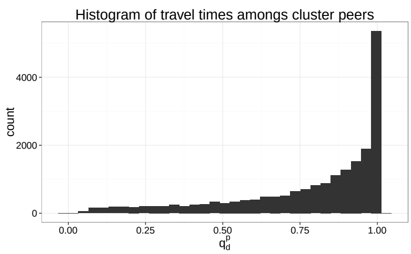
The distribution of the q_l^p scores (Figure 6.4) are less clustered around 1. This is probably due to the heuristic used in selecting a route in the baseline scenario. The vehicles only evaluate the routes based on the travel time, not based on the distance. As the traffic network becomes saturated, drivers start looking for routes that are much longer to avoid traffic.



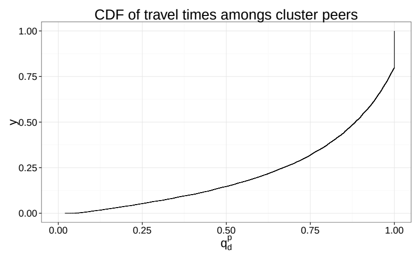
(a) q_d^p distribution in Leuven



(b) q_d^p Cummulative Density Function (CDF) in Leuven



(c) q_d^p distribution in Flanders



(d) q_d^p CDF in Flanders

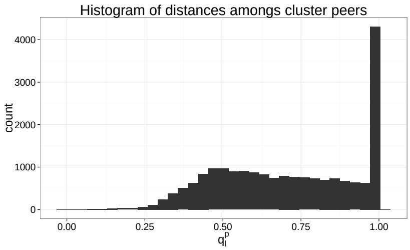
Figure 6.3: The q_d^p values for the undisturbed baseline simulation shown as a histogram and a CDF.

6.2.2 Analysis of the AntTIS routes

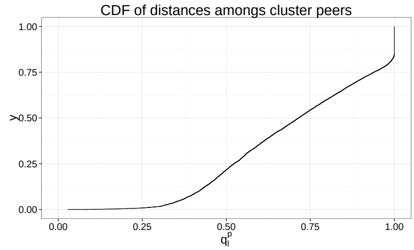
This section analyses the routes given to drivers when guided by AntTIS in the undisturbed scenarios. In all these simulations, a 100% participation rate is assumed. The analysis in this section has two goals: (1) compare the quality of the routes provided by AntTIS to those from the baseline and (2) examine the differences between the different simulation runs.

The first goal will look at the travel time and distance distribution for all routes provided by the AntTIS solution and compare these distributions with the distributions obtained in the baseline simulation. The q^p scores of the routes in the AntTIS case will be compared with those obtained in the baseline. The q^b scores will be calculated for all routes in the AntTIS will be calculated and from these values, a comparison between the baseline and AntTIS can be made.

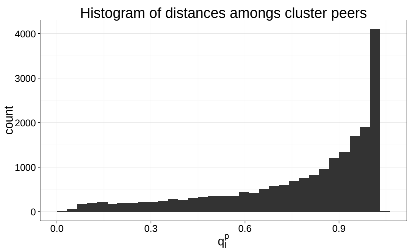
The second goal will look at the distribution of the q^b scores not to compare the quality with the baseline, but to assess the difference between the different simulation runs. As explained in Section 6.1, all simulations are repeated 30



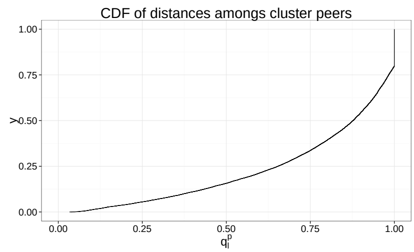
(a) q_l^p distribution in Leuven



(b) q_l^p CDF in Leuven



(c) q_l^p Flanders



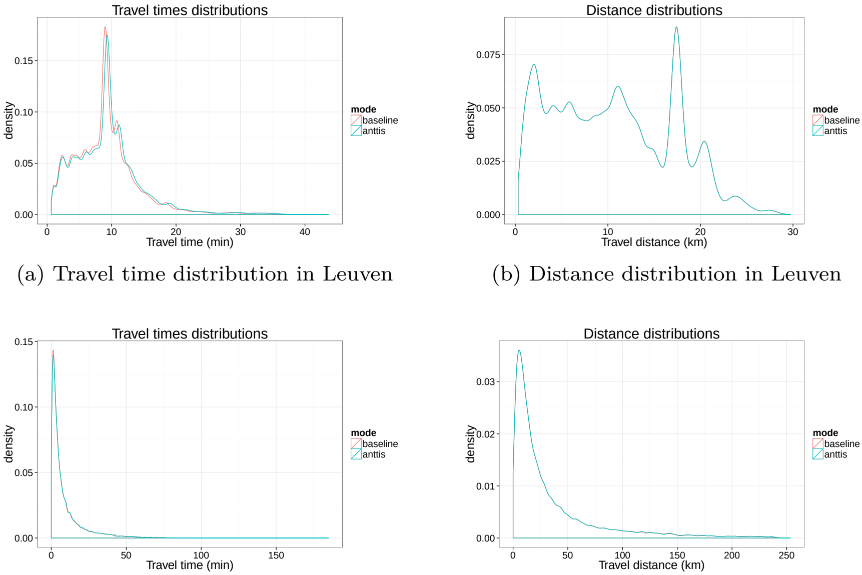
(d) q_l^p CDF in Flanders

Figure 6.4: The q_l^p values for the undisturbed baseline simulation shown as a histogram and a CDF.

times to account for non-determinism in the AntTIS system. The influence of the de-aggregation step is no longer analysed. The bias introduced by this step was already determined to be minimal in the previous section.

Figure 6.5 shows the distributions of both the travel time and distance for both the baseline and the AntTIS guided simulation for both the Leuven and the Highway scenario. From Figures 6.5a and 6.5c it is clear that the travel times experienced by the drivers in the AntTIS solution are slightly longer than those experienced by the drivers in the baseline scenario. This is due to the fact that the drivers in the baseline scenario have almost perfect knowledge of the traffic conditions they will encounter due to the iterative process that leads to that route assignment. In the AntTIS case, all drivers depart with no knowledge. Their decisions are guided by the link traversal predictions provided by the AntTIS system.

The distribution of the distances shown in Figures 6.5b and 6.5d show that there is very little difference in the overall distribution of the distances travelled in both simulations. Based on the travel time distributions and the advantage



(a) Travel time distribution in Leuven

(b) Distance distribution in Leuven

(c) Travel time distribution in Flanders

(d) Distance distribution in Flanders

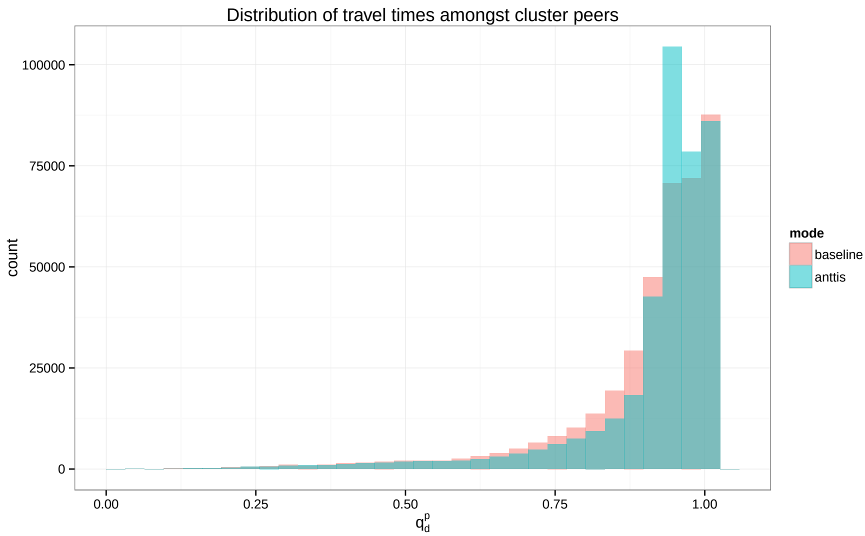
Figure 6.5: Distribution of the travel time and the distance for all routes in both the undisturbed Leuven and the Highway scenario.

the baseline drivers had one could expect shorter trips in the AntTIS simulation. However, the results do not confirm this.

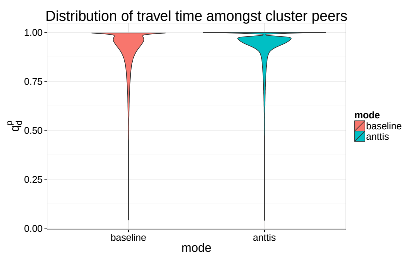
The q^p metrics of the routes from both the baseline and the AntTIS case can also be compared. Figures 6.6-6.7 compare the distribution of q_d^p scores for baseline case and the AntTIS case in respectively the Leuven and the Highway scenario. The figures show that in the baseline case, the values are clustered closer to 1, indicating that the equality within a cluster is greater.

Figures 6.8 and 6.9 again confirm that there is little difference in travelled distance between the routes in the baseline case and the AntTIS case.

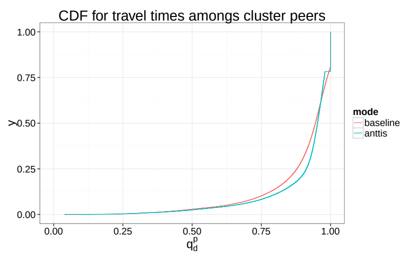
The distribution of the q_d^b and q_l^b scores give the best comparison between the quality of the baseline and the AntTIS guided simulations. Figure 6.10 shows all obtained distributions without aggregating over all de-aggregated runs. There are three trends visible in the figures: (1) again, the impact of the de-aggregation is negligible, (2) the q_l^b values describing the distance are centered on 1 and (3) the q_d^b values describing the travel time are centered slightly above 1.



(a) q_d^p histogram for Leuven

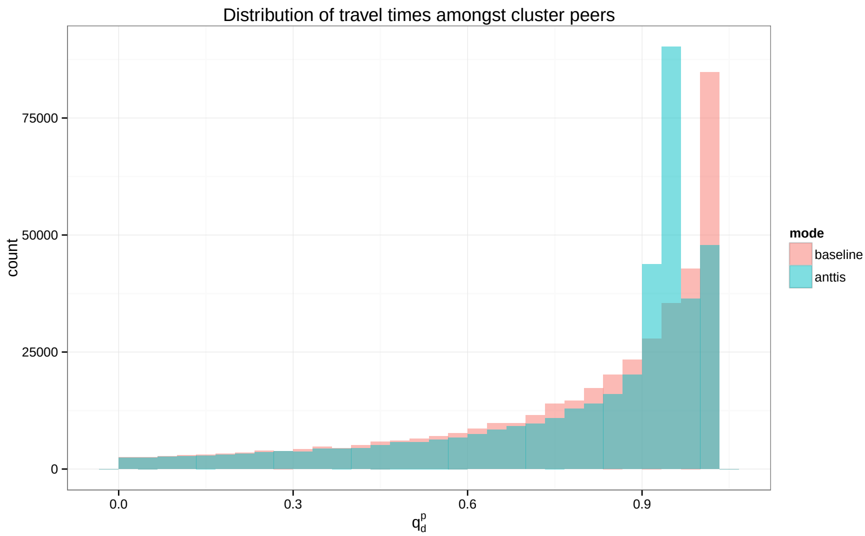


(b) q_d^p violin plot for Leuven

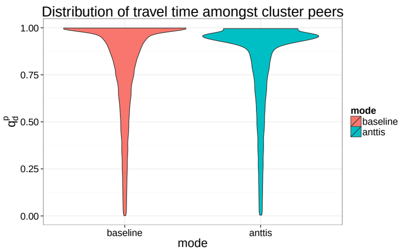


(c) q_d^p CDF plot for Leuven

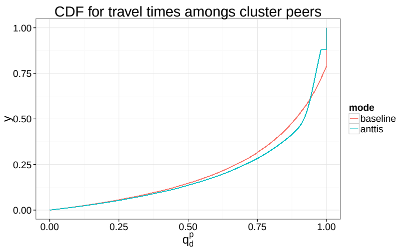
Figure 6.6: Comparison of the q_d^p scores describing the quality of the travel time amongst a cluster of similar routes for the baseline case and the AntTIS case in both the undisturbed Leuven and the Highway scenario



(a) q_d^p histogram for Flanders

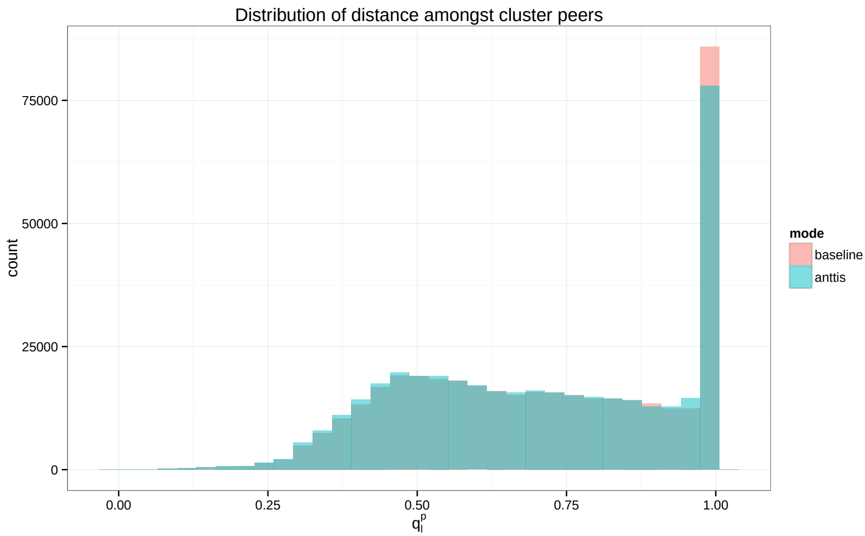


(b) q_d^p violin plot for Flanders

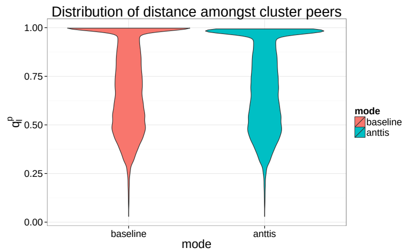


(c) q_d^p CDF plot for Flanders

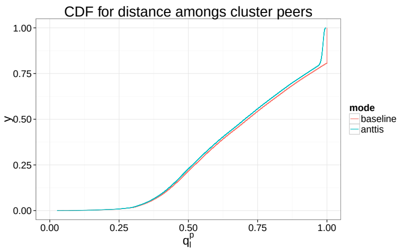
Figure 6.7: Comparison of the q_d^p scores describing the quality of the travel time amongst a cluster of similar routes for the baseline case and the AntTIS case in both the undisturbed Leuven and the Highway scenario



(a) q_l^p histogram for Leuven

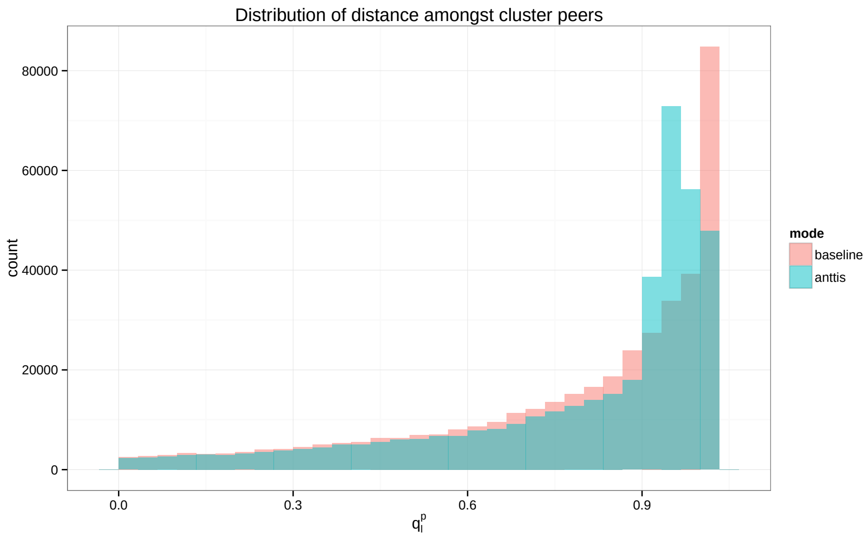


(b) q_l^p violin plot for Leuven

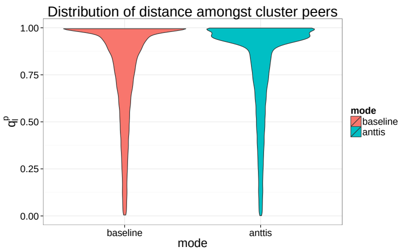


(c) q_l^p CDF plot for Leuven

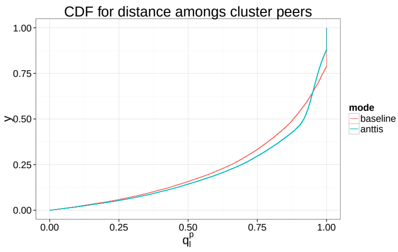
Figure 6.8: Comparison of the q_l^p scores describing the quality of the travel distance amongst a cluster of similar routes for the baseline case and the AntTIS case in both the undisturbed Leuven and the Highway scenario



(a) q_l^p histogram for Flanders

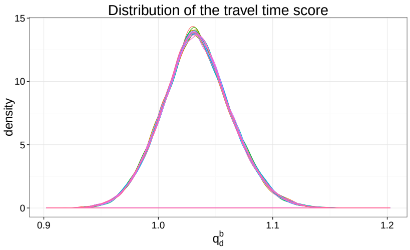


(b) q_l^p violin plot for Flanders

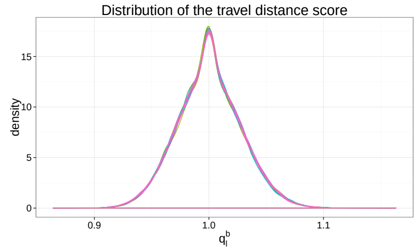


(c) q_l^p CDF plot for Flanders

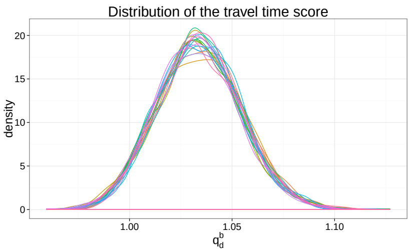
Figure 6.9: Comparison of the q_l^p scores describing the quality of the travel distance amongst a cluster of similar routes for the baseline case and the AntTIS case in both the undisturbed Leuven and the Highway scenario



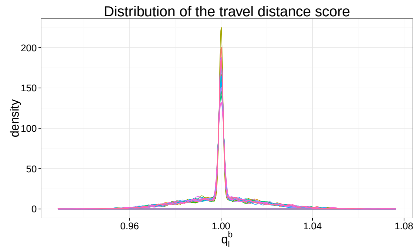
(a) q_d^b distributions for Leuven



(b) q_l^b distributions for Leuven



(c) q_d^b distributions for Flanders

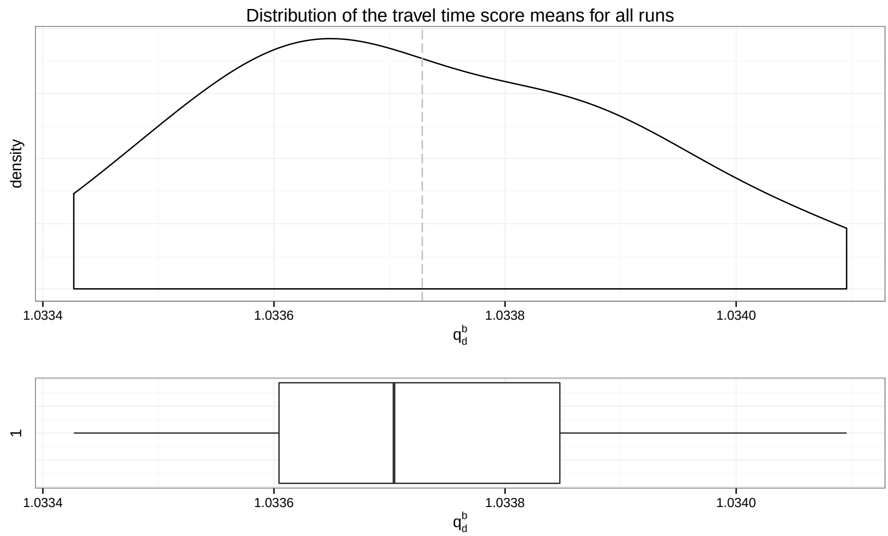


(d) q_l^b distributions for Flanders

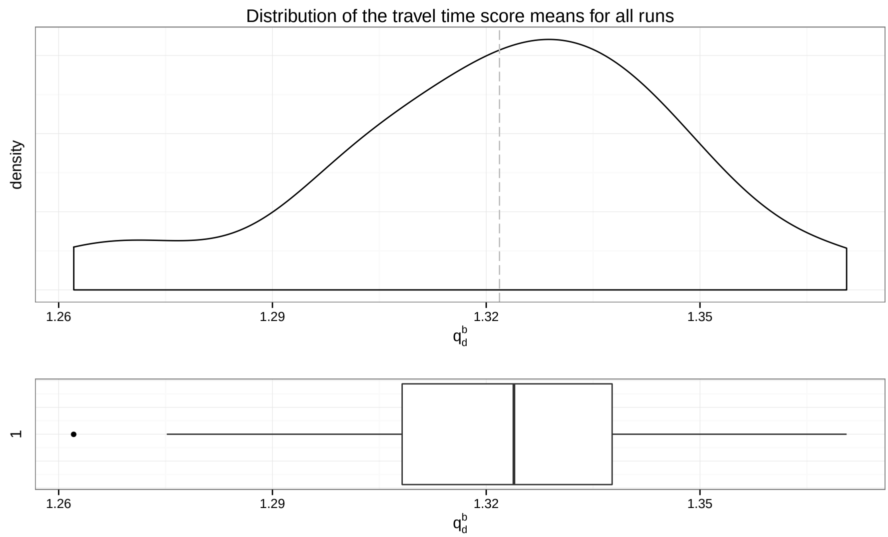
Figure 6.10: Distributions of the q_d^b and q_l^b scores for the results obtained in both the undisturbed Leuven and the Highway scenario. Every distribution corresponds to one de-aggregated version. A summary of the data can be found in Table 6.1

This again confirms earlier observations that the travelled distances between the baseline and the AntTIS case do not differ very much, they average on 1.000 with a standard deviation of 0.032 for Leuven and 1.000 with a standard deviation of 0.019 for Flanders (Table 6.1).

The travel times in the AntTIS case are slightly higher than those in the baseline case. The average q_d^b score for Leuven is 1.034 with a standard deviation of 0.031 and 1.034 with a standard deviation of 0.020 in Flanders. Figure 6.11 further emphasizes the increase in travel time. Here the distribution of all mean q_d^b values over all runs is shown. The distribution is not normal, it is skewed to the right.



(a) q_d^b distribution for Leuven



(b) q_d^b distribution for Flanders

Figure 6.11: Overall distribution of q_d^b values for both the undisturbed Leuven and Highway scenarios. The grey dashed line in the density plot indicates the average. A summary of the data can be found in Table 6.1

	mean	std dev	N
q_d^b	1.034	0.031	30
q_l^b	1.000	0.028	30

(a) Results for Leuven

	mean	std dev	N
q_d^b	1.034	0.020	30
q_l^b	1.000	0.019	30

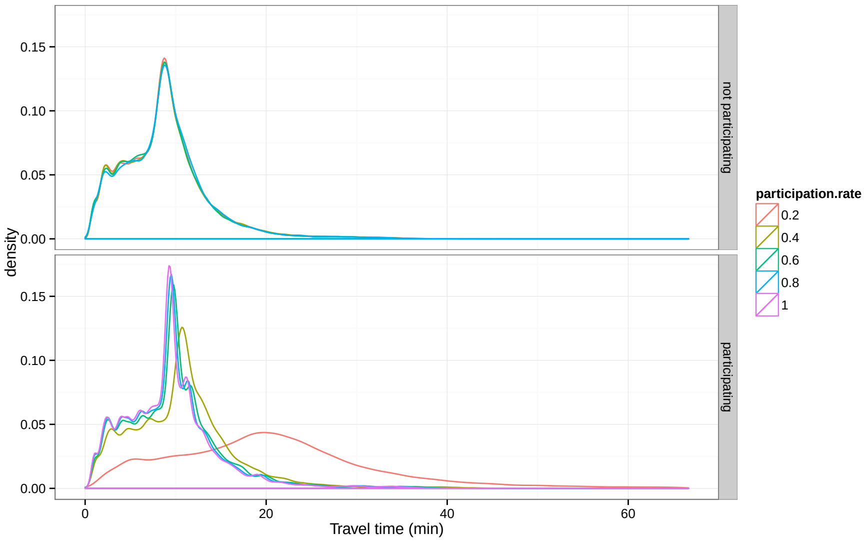
(b) Results for Flanders

Table 6.1: Characteristics of the q_d^b and q_l^b metrics for the undisturbed Leuven and Highway scenarios

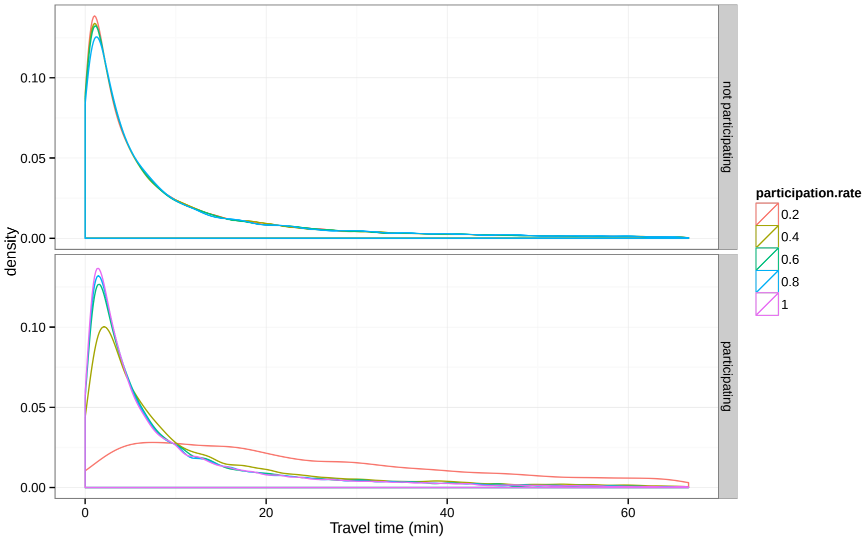
6.2.3 Analysis of the influence of participation rates

This section looks at the impact of partial participation on the performance of the AntTIS system. The analysis focusses on the travel time and the q_d^b and q_d^p metrics. The differences in the distances between the baseline simulation and the AntTIS simulations where not that significant.

The distribution of the travel times is shown in Figure 6.12. For the 20% participation rate, the difference in travel times is large. Table 6.2 shows the q_d^b values for the various participation rates. The decline in route quality for the 20% participation rate case becomes even more apparent here. Travel times are on average at least two times longer than those in the baseline case. For the 40% participation rate, the shift towards the right is noticeable, but not as pronounced as in the 20% case.



(a) Travel time distribution for Leuven



(b) Travel time distribution for Flanders

Figure 6.12: Distribution of the travel times for both participating and non-participating vehicles in the experiments with varying participation rates. Results are for the undisturbed Leuven and Highway scenario with varying participation rates.

part. rate	$\mu_{\mathbf{np}}$	$\sigma_{\mathbf{np}}$	$\mathbf{N_{np}}$	$\mu_{\mathbf{p}}$	$\sigma_{\mathbf{p}}$	$\mathbf{N_p}$
100%	–	–	0	1.034	0.031	33838200
80%	1.026	0.059	6767640	1.054	0.032	27070560
60%	1.028	0.058	13535280	1.082	0.035	20302920
40%	1.030	0.059	20302920	1.196	0.062	13535280
20%	1.032	0.059	27070560	2.328	0.414	6767640

(a) q_d^b results for Leuven

part. rate	$\mu_{\mathbf{np}}$	$\sigma_{\mathbf{np}}$	$\mathbf{N_{np}}$	$\mu_{\mathbf{p}}$	$\sigma_{\mathbf{p}}$	$\mathbf{N_p}$
100%	–	–	0	1.034	0.020	440390700
80%	0.997	0.098	88078140	1.059	0.021	352312560
60%	0.990	0.099	176156280	1.114	0.023	264234420
40%	0.990	0.098	264234420	1.438	0.040	176156280
20%	0.999	0.098	352312560	7.499	0.483	88078140

(b) q_d^b results for Flanders

Table 6.2: Characteristics of the q_d^b metric for the undisturbed Leuven and Highway scenarios under various participation rates. The population mean μ, standard deviation σ and size N for both the participating p and non-participating np populations.

6.2.4 Analysis of the traffic predictions

The route guidance in AntTIS relies heavily on its ability to predict future traffic states. One of the hypotheses put forward in Section 5.1 is that AntTIS is able to predict future traffic states.

To validate this hypothesis the predictions of some of the links are logged during the different simulations. Collecting all predictions from all links would result in too much data to process as the AntTIS system continuously hands out predictions.

The quality of the predictions is checked using the relative absolute error, e_r of the predicted values:

$$e_r = \|\frac{p_{ltt} - m_{ltt}}{m_{ltt}}\| \tag{6.1}$$

Where p_{ltt} is the predicted link traversal time and m_{ltt} is the measured link traversal time. Many performance metrics for accuracy in forecasting exist [62]. However, almost all of them describe the overall result of the ANN: the performance of the ANN after training evaluated over a training set. In the metric described above, we take out the aggregation from the mean absolute percentage error (MAPE) and only keep the absolute and relative aspect of this performance metric.

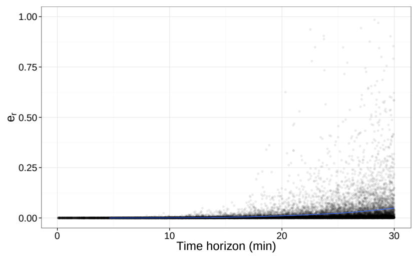
We again choose a relative metric to analyse the performance of the predictions. The different links in the scenarios have different characteristics. Different speed limits, different lengths and different usage levels make comparing predictions of different links difficult.

The relative absolute error on the predictions is shown in Figure 6.13 and 6.14. The time horizon, how much in advance the prediction is made, is on the x-axis, the relative absolute error on the y-axis.

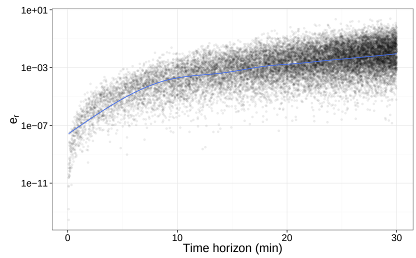
As seen from the points representing individual predictions, there is a lot of variability on the quality of the predictions. Even for small time horizons. The values shown here are recorded over the entire simulation on a representative sample of roads. Early in the simulation, some of the ANN may need more training. Some sparsely used roads might have very little training data.

The impact of the evolution of the ANNs on the quality of the predictions is shown in Figure 6.15. Especially in the Flanders scenario (Figure 6.15b), the predictions strongly improve over time. The improvement in the Leuven scenario (Figure 6.15a) is less clear, but still present.

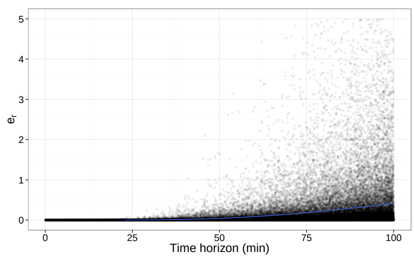
The role of the ANN as a mapping function that converts the intention levels into travel time predictions is reaffirmed in Figure 6.16. A correlation between



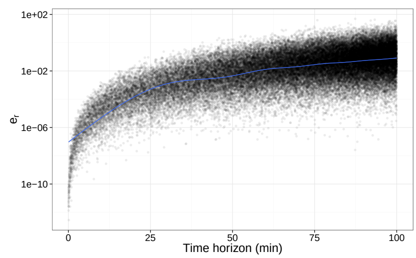
(a) Error on travel time predictions for Leuven



(b) Error on travel time predictions for Leuven



(c) Error on travel time predictions for Flanders



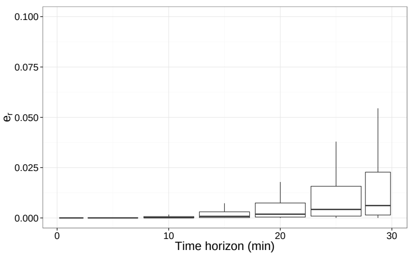
(d) Error on travel time predictions for Flanders

Figure 6.13: Absolute relative error e_r on the travel time predictions for the undisturbed scenario in both the Leuven and the Highway scenario. The x-axis shows the time horizon, how far in time the prediction is made, while the y-axis shows the absolute value of the relative error. All predictions logged during the simulation are plotted along with a trendline.

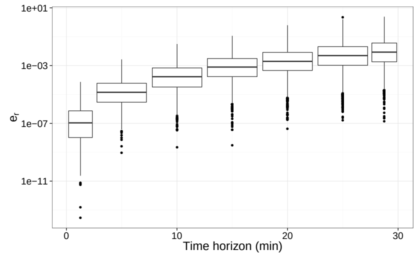
the intention levels (left) and the predicted travel times (right) is clearly visible. The left figures show the intention levels recorded for four different roads[1]. Each line represents a different time offset. For example, the 5 minute offset shows the intention level for time t known by the Infrastructure Agent at $t - 5min$. The prediction graphs on the right also include the actual measured travel time.

The graphs in Figure 6.16 confirm the observations made based on Figure 6.13. Predictions in the near future are accurate, but predictions further ahead can be unreliable. Based on Figure 6.16, we can conclude that this unreliability is not caused by the ANN based mapping of intention levels onto travel times, but rather is caused by the unreliability of the intention levels so far ahead.

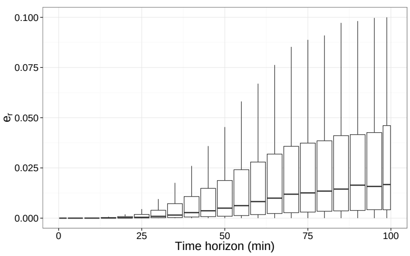
[1] Roads are selected based on the dynamics of the intention levels.



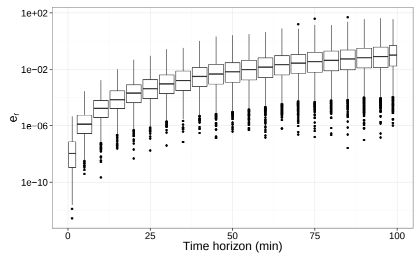
(a) Error on travel time predictions for Leuven



(b) Error on travel time predictions for Leuven



(c) Error on travel time predictions for Flanders



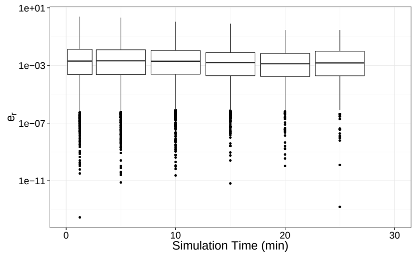
(d) Error on travel time predictions for Flanders

Figure 6.14: Absolute relative error e_r on the travel time predictions for the undisturbed scenario in both the Leuven and the Highway scenario. These graphs group all predictions made based on the time horizon and for each group shows the distribution of that group as a boxplot. In Figure 6.14a and 6.14c the outliers are not shown.

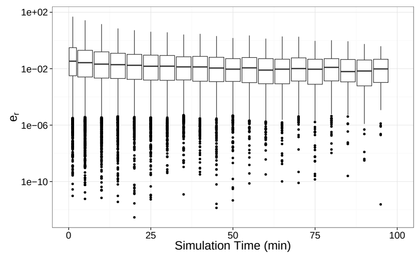
The ability of AntTIS to predict travel times relies heavily on the participation rate. If an insufficient portion of the drivers participates in the system, the intention levels on which the predictions are based become incorrect and the ANNs will have to do a lot of extrapolation.

Figure 6.17 shows the impact of the participation rates on the link traversal time predictions. The quality of the predictions for the 20% and 40% percent participation cases are a possible explanation for the poor quality of the routes assigned in those experiments.

As mentioned in Section 5.5.1, the often accurate predictions of the travel times can be partly attributed to the simplicity of the simulation model used to evaluate the approach. In more complex scenarios, mapping the intention levels onto the travel times might require more sophisticated approaches. However,



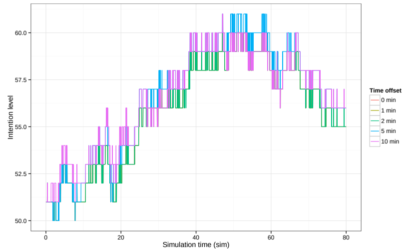
(a) Error on travel time predictions for Leuven



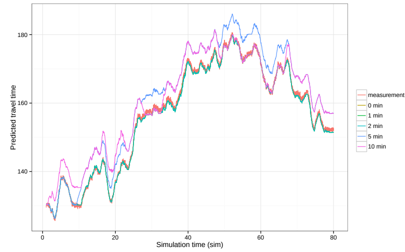
(b) Error on travel time predictions for Flanders

Figure 6.15: Absolute relative error e_r on the travel time predictions for the undisturbed scenario inboth the Leuven and Highway scenario over time. These graphs show how the prediction error decreases over time as the ANN become better at predicting link traversal times.

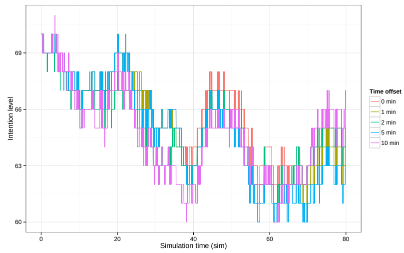
as long as there is a strong correlation between the intention levels and the experienced travel times, the relationship between both can be used to predict link traversal times. How the relationship is modelled, through the use of machine learning as in this thesis or through explicit traffic modelling and possibly simulation, does not influence the overall system.



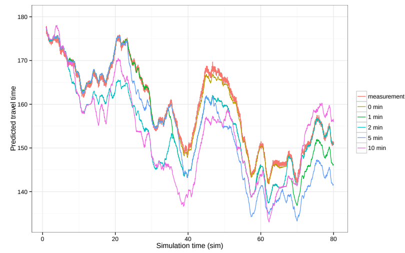
(a) Intentions on Road 1



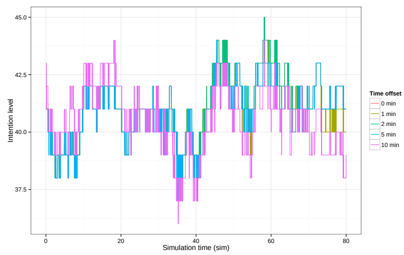
(b) Predictions on Road 1



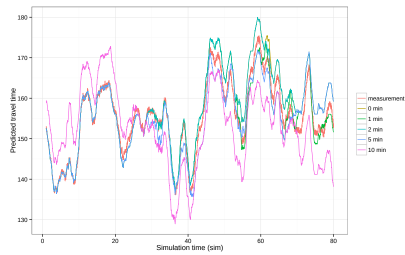
(c) Intentions on Road 2



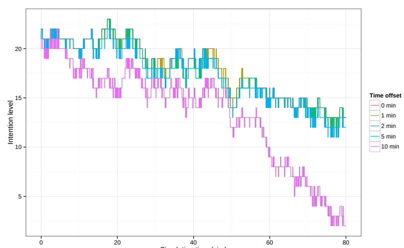
(d) Predictions on Road 2



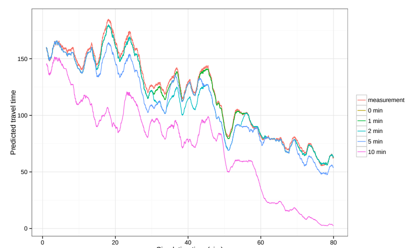
(e) Intentions on Road 3



(f) Predictions on Road 3

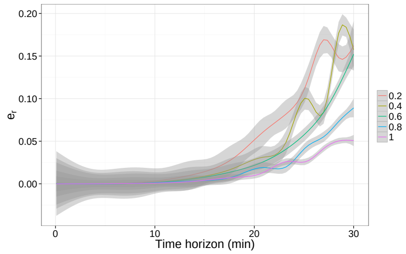


(g) Intentions on Road 4

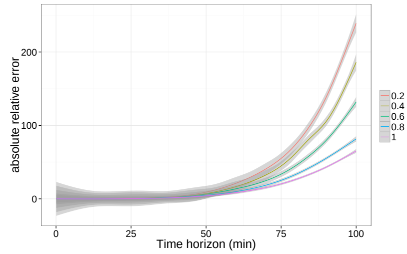


(h) Predictions on Road 4

Figure 6.16: Intention levels (left) and predictions (right) for four roads. The graphs show the intentions and predictions throughout the simulation for different time offsets.



(a) Error on travel time predictions for Leuven



(b) Error on travel time predictions for Flanders

Figure 6.17: Absolute relative error on the travel time predictions for the undisturbed scenario in both the Leuven and the Highway scenario. The x-axis shows the time horizon, the y-axis shows the absolute value of the relative error. Only the trend lines are shown as the points for the different participation rates heavily overlap.

6.2.5 Conclusion for undisturbed scenarios

The analyses in this section lead to the following conclusions for the undisturbed experiment:

- The non-determinism in both the de-aggregation and the AntTIS simulations do not cause much variance in the results.
- In the baseline simulation, most trips within a cluster of similar trips have similar travel times and distances. This validates the meaningfulness of comparing other results with the baseline as it appears to be a user optimal equilibrium.
- In the AntTIS simulation, the distances travelled by the guided vehicles are roughly equal to the distance travelled in the baseline simulation.
- In the AntTIS simulation, the travel times experienced by the guided vehicles are longer than those in the baseline case. The equality within the clusters is also less than observed in the baseline scenario.
- In the undisturbed scenario, AntTIS is capable of predicting future traffic conditions. As the time horizon increases, the quality of the predictions decrease.
- The participation rate has a strong influence on the quality of the prediction quality.

The advantage of the smaller travel durations in the baseline scenario can be explained by the almost perfect knowledge the drivers have in that scenario. The baseline scenario is the result of an iterative process in which the drivers always get the real traffic results observed in the previous step.

In the AntTIS scenario, the iterative process occurs online. During the route guidance intention levels are continuously being updated, as long as these updates cause significant change in the predictions, the road users will change their routes. The online dynamic behavior has a cost and the results observed in this section have highlighted that cost. In other scenarios where the traffic network itself displays a certain amount of dynamism, the dynamic nature of the AntTIS system will become a benefit instead of drawback.

6.3 Disturbed Experiments

The experiments described in this section are experiments in which the traffic scenario is slightly altered from the base scenarios. For the baseline simulation, the alternations are not present during the iterative training process. The iterative training process is still based on the unaltered scenario. The routes assigned to the vehicles are evaluated using a slightly altered scenario. The routes in the baseline scenario do not change during the simulation.

Two types of disturbances are tested: disturbances in the traffic flow and disturbances in the traffic network. For the disturbances in the traffic flow the traffic demand is altered. The vehicle counts for certain rows in the macroscopic origin-destination matrix are increased to simulate a sudden increase in traffic. For the disturbances in the traffic network, the capacity of certain links in the network are reduced. This is to simulate incidents occurring on those links.

Based on the simulation results for both types of disturbances, the following analyses will be performed:

- **Analysis of the impact of the disturbances on the baseline scenario** The quality of the baseline routes, when evaluated on the altered scenario will be compared with the quality of the routes advised by the AntTIS system.
- **Analysis of the impact of the participation rate** The non-participating drivers in the simulations with AntTIS guidance are still basing their route choices based on the wrong assumptions. How this portion of the driver population affects the overall quality of the assigned routes in the AntTIS guided case will be analysed.
- **Analysis of the traffic on an individual road** The vehicle inflow, intention levels and predictions for a road have been analyzed to see how AntTIS affects the route choice of vehicles.

For these experiments less analyses are done compared to the undisturbed experiment. This is because the quality of the traffic predictions should not be influenced by the disturbances, because the impact of the de-aggregation has already been analysed. The analyses will focus less on the outcome of the two individual simulations, as was the case for the undisturbed experiment, but will focus more on comparing the baseline with the AntTIS guided case.

	mean	std dev	N
q_d^b	0.809	0.192	30
q_l^b	1.004	0.070	30

(a) Results for Leuven

	mean	std dev	N
q_d^b	0.760	0.223	30
q_l^b	1.008	0.094	30

(b) Results for Flanders

Table 6.3: Characteristics of the q_d^b and q_l^b metrics for the network disturbed Leuven and Highway scenarios

6.3.1 Network Disturbances

This section discusses the experiments in which the traffic network was altered.

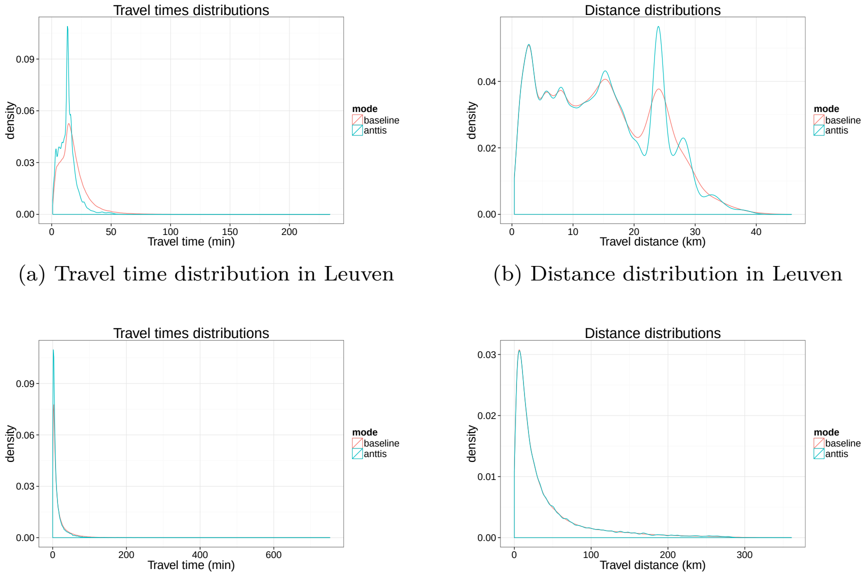
For the Leuven scenario, the capacity of certain links in the outer and inner beltway around Leuven (De Geldenaaksevest near Tiensepoort and the Rennessingel near Brusselsesteenweg) was reduced by a factor 2. For the Highway scenario, the capacity of the outer beltway around Brussels (E40 near Zaventem), the highway between Antwerp and Brussels (E19 near Zemst) and the highway between Brussels and Ghent (E40 near Aalst) were reduced by a factor 2.

Analysis of the baseline

The distribution of the travel times and distances for the network disturbed Leuven and Highway scenarios (Figure 6.18 differ from the ones observed in the undisturbed scenario. The travel times observed in the baseline scenario have increased. For the distances, the shape of the distribution has changed, but the mean appears to be the same.

Figure 6.19 confirms these observations. The q_d^b values are clustered around a mean value of 0.809 with a standard deviation of 0.192 for Leuven and a mean value of 0.760 with a standard deviation of 0.223 for Flanders (Table 6.3).

Figure 6.20a shows the distribution of q_d^b values for the overall results and compares it with the distribution observed in the undisturbed simulation. Here it is clearly shown that the routes advised by the AntTIS lead to experienced travel times that are on average much lower than in the baseline scenario.



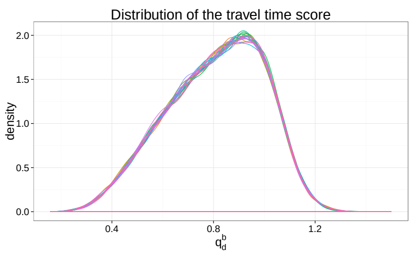
(a) Travel time distribution in Leuven

(b) Distance distribution in Leuven

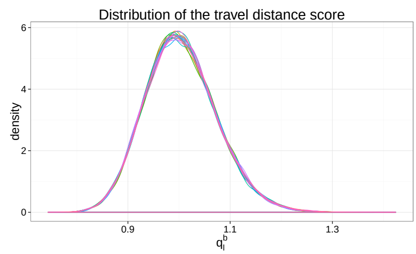
(c) Travel time distribution in Flanders

(d) Distance distribution in Flanders

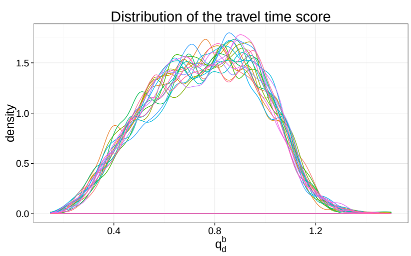
Figure 6.18: Distribution of the travel time and the distance for all routes in both the Leuven and the Highway scenario with network disturbances.



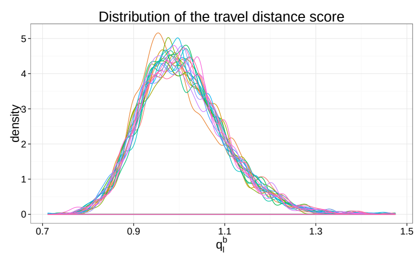
(a) q_d^b distributions for Leuven



(b) q_l^b distributions for Leuven

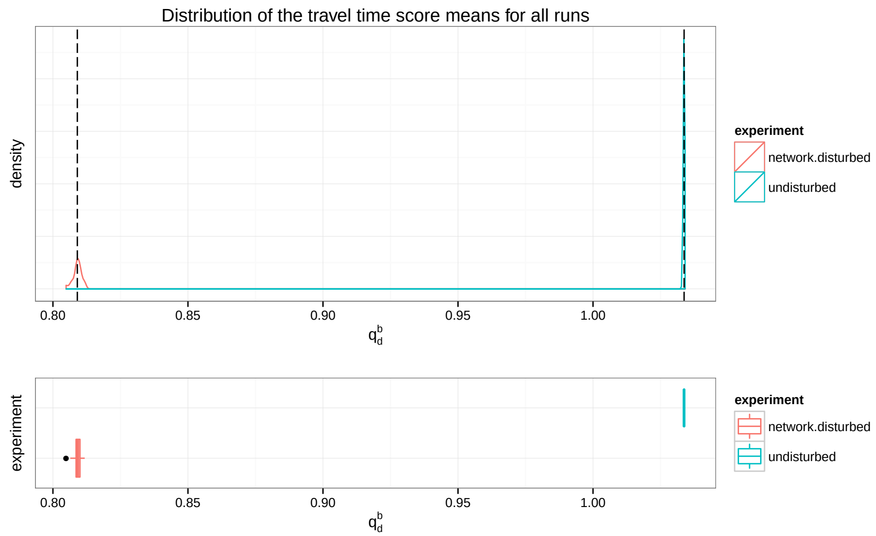


(c) q_d^b distributions for Flanders

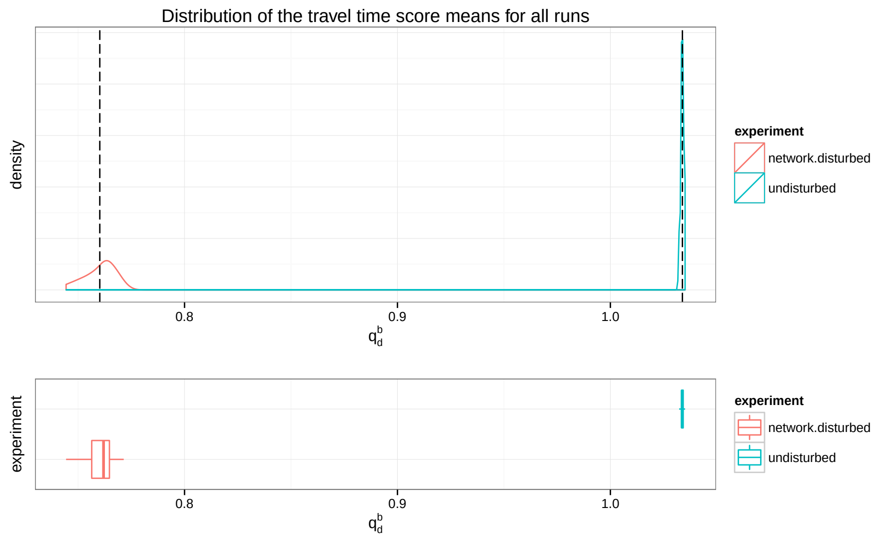


(d) q_l^b distributions for Flanders

Figure 6.19: Distributions of the q_d^b and q_l^b scores for the results obtained in both the network disturbed Leuven and the Highway scenario. Every distribution corresponds to one de-aggregated version. The characteristics of the distributions are summarized in Table 6.3



(a) q_d^b distribution for Leuven



(b) q_d^b distribution for Flanders

Figure 6.20: Overall distribution of q_d^b values for the network disturbed Leuven and Highway scenario. The grey dashed line in the density plot indicates the average.

part. rate	$\mu_{\mathbf{np}}$	$\sigma_{\mathbf{np}}$	$\mathbf{N_{np}}$	$\mu_{\mathbf{p}}$	$\sigma_{\mathbf{p}}$	$\mathbf{N_{p}}$
100%	–	–	0	0.809	0.192	33838200
80%	0.992	0.049	6767640	0.825	0.195	27070560
60%	0.994	0.050	13535280	0.846	0.201	20302920
40%	0.996	0.050	20302920	0.935	0.225	13535280
20%	0.998	0.050	27070560	1.820	0.542	6767640

(a) q_d^b results for Leuven

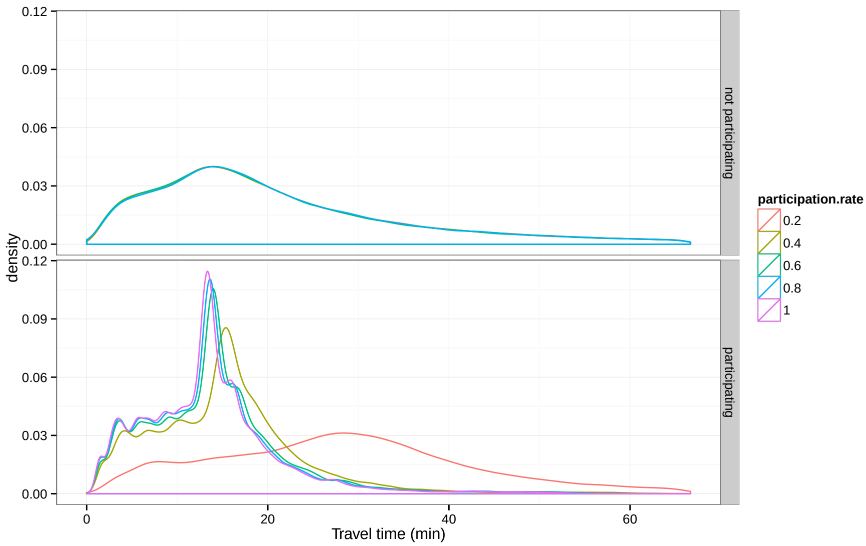
part. rate	$\mu_{\mathbf{np}}$	$\sigma_{\mathbf{np}}$	$\mathbf{N_{np}}$	$\mu_{\mathbf{p}}$	$\sigma_{\mathbf{p}}$	$\mathbf{N_{p}}$
100%	–	–	0	0.760	0.222	440390700
80%	0.990	0.098	88078140	0.777	0.229	352312560
60%	0.993	0.098	176156280	0.816	0.240	264234420
40%	0.995	0.099	264234420	1.051	0.311	176156280
20%	0.997	0.098	352312560	5.530	1.675	88078140

(b) q_d^b results for Highway

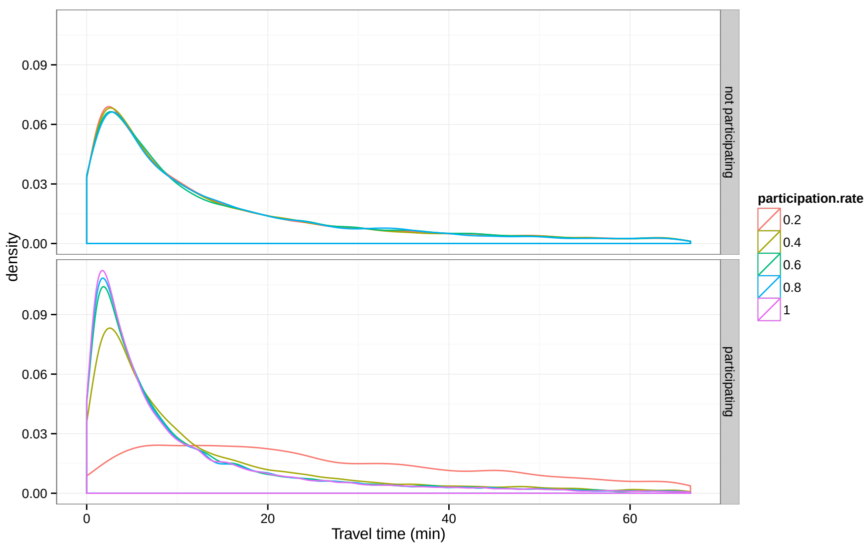
Table 6.4: Characteristics of the q_d^b metric for the network disturbed Leuven and Highway scenarios under various participation rates. The population mean μ, standard deviation σ and size N for both the participating p and non-participating np populations.

Analysis of the participation rates

Figure 6.21 shows the impact of partial participation on the distribution of travel times in the network disturbed scenarios. For participation rates above the 40% participation rate threshold the travel times of the AntTIS routes remain better than those in the baseline scenario. For 40% and especially 20% participation rates, the benefits of using AntTIS over baseline disappears. For the 20% participation rate, drivers are still better of relying on their incorrect historical information than relying on the routes provided by AntTIS. The q_d^b values in Table 6.4 confirm these observations.



(a) Travel time distribution for Leuven



(b) Travel time distribution for Flanders

Figure 6.21: Distribution of the travel times for both participating and non-participating vehicles in the experiments with varying participation rates with the network disturbed Leuven and Highway scenarios.

Analysis of one bottleneck

This section does not look at the results of the overall traffic assignment and instead focusses on a single road. By analyzing the traffic that makes use of this road we look at the impact the network disturbance has on the route choice of the vehicles.

This section analyses the traffic flow, ANN based predictions and intention levels for one of the bottlenecks in the Leuven scenario. More specifically, the route choices of the vehicles that used the link at Geldenaaksevest during the undisturbed experiment are analysed and compared with the route choices in the network disturbed experiment.

Contrary to the other sections in this chapter, this section only looks at one simulation of one of the microscopic scenarios. Results of the baseline solution are not included since in the baseline solution vehicles do not change their routes. The analysis only covers one of the two bottlenecks that are introduced in the network.

Figure 6.22 shows the route choice of vehicles interested in the congested link. The figure shows the vehicles entering the link in the undisturbed scenario. In the network disturbed scenario, the route choice of those same vehicles is examined. The vehicles are divided into two groups: those that still use the congested link and vehicles that choose an alternative. The set of alternatives considered by the group of vehicles is too diverse to enumerate, so all alternatives are aggregated into one group.

A comparison of the graphs in Figure 6.22 shows that when the disturbance is introduced, the number of vehicles choosing the congested link is reduced by more than half. The vehicles not choosing the link choose the alternatives. The reason for this shift is shown in Figure 6.23. The graph in Figure 6.23 shows the predictions generated by AntTIS for the link in both the disturbed and undisturbed scenario. We see that in the network disturbed scenario the predictions are much higher than in the undisturbed scenario. The increase that this causes in the estimated time of arrival (ETA) for the evaluated routes causes many vehicles to reconsider and choose one of the alternative routes.

To analyze whether an equilibrium is formed between the original route and the alternative routes we measure the travel time of all vehicles that passed the bottleneck in the undisturbed scenario and that pass both points **A** and **B** in Figure 6.24. The measured travel times are shown in Figure 6.25. The travel times experienced by vehicles that still use the bottleneck and the travel times of the vehicles using alternative routes are not identical, but are of the same order of magnitude.

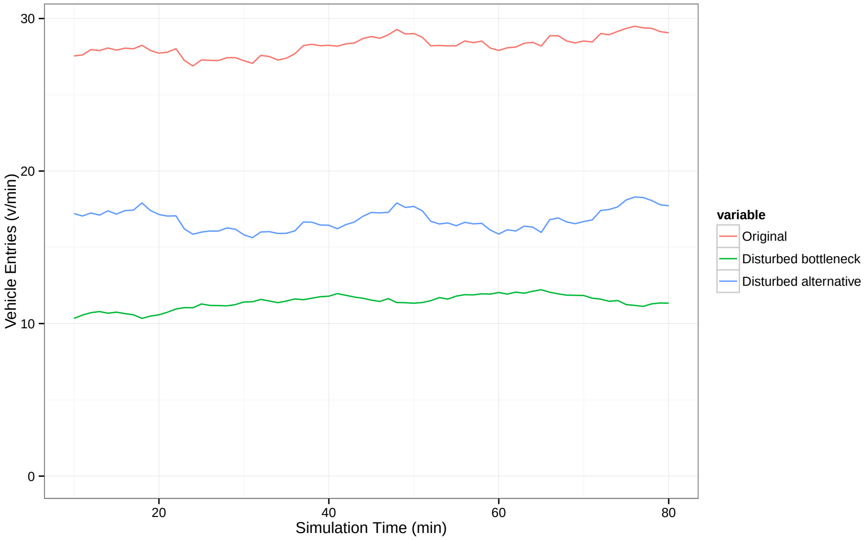


Figure 6.22: The route choice of the vehicles interested in the congested link. The figure shows the inflow of vehicles into the link in the undisturbed scenario. In the network disturbed scenario, the figure shows the inflow of vehicles into the link and the number of vehicles choosing for an alternative route.

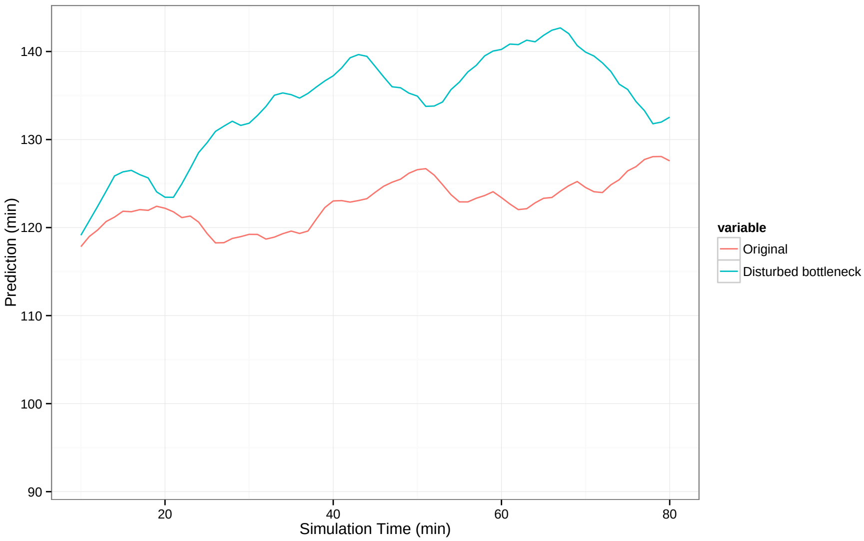


Figure 6.23: The predictions generated by the ANN trained on the link. The predictions shown in this figure are all predictions generated with a prediction horizon of 3 minutes. The predictions made by the ANN in the network disturbed case are much higher than the ones generated for the undisturbed case. These predictions are what causes the drivers to consider the alternative routes

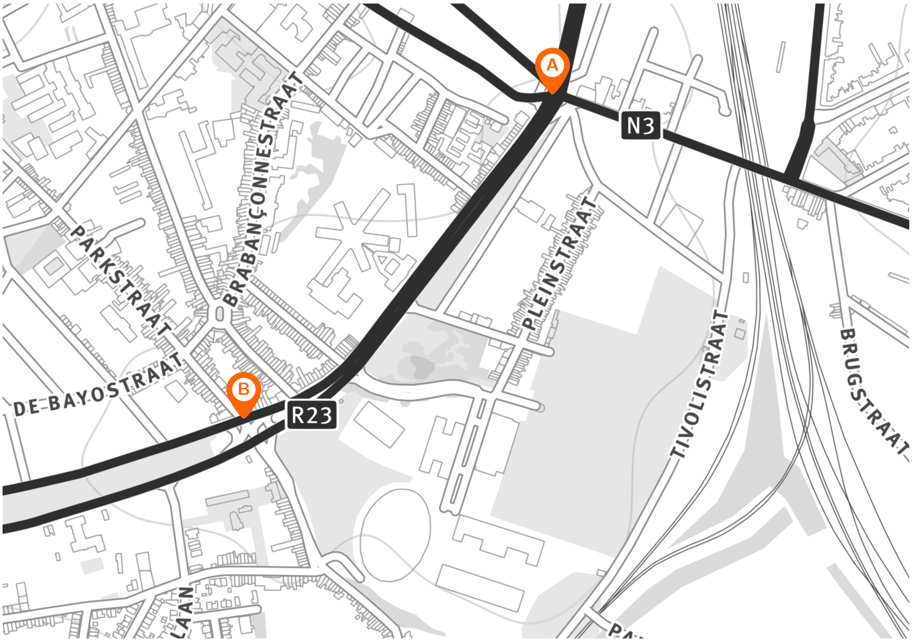


Figure 6.24: Network around the bottleneck. Points **A** and **B** show the locations on which the travel time measurements are based. Map data © Mapbox © OpenStreetMap.

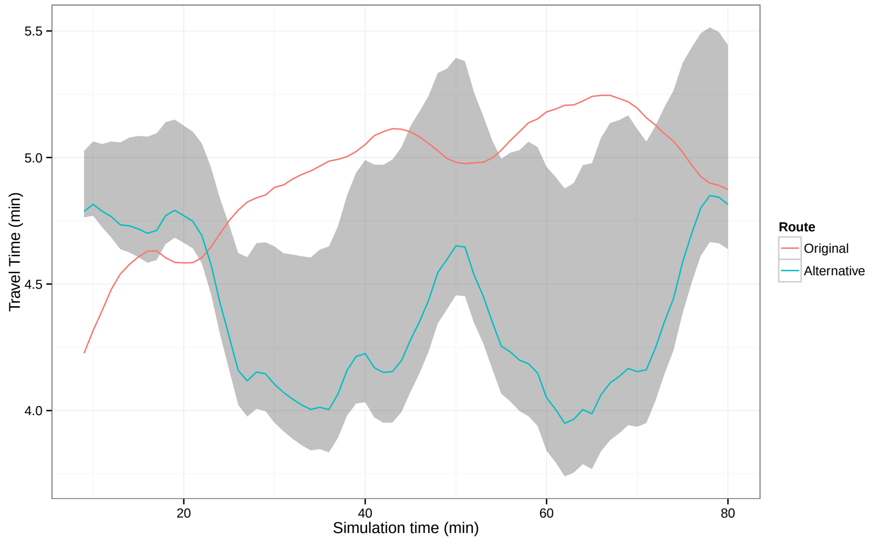


Figure 6.25: Travel times between points **A** and **B** for vehicles that use the bottleneck in the undisturbed scenario *and* pass through both points **A** and **B** as shown in Figure 6.24. The solid lines show the mean recorded travel times for the vehicles, the grey ribbon shows the total range of the travel times experienced on all alternative routes. The total range of the travel times on the original route is much smaller. The experienced travel times are of the same order of magnitude.

6.3.2 Flow Disturbances

For the experiments described in this section the macroscopic origin-destination matrix representing the traffic demand is altered. The vehicle counts for certain lines in the origin destination matrix are multiplied with a factor 1.5. The origin-destination pairs are selected based on the location of their origin or destination. Pairs are selected until the overall increase in traffic approximates 5%.

For the Leuven scenario, the counts for all OD pairs with an origin or destination close to the Konging Albertlaan are increased. The overall increase in traffic is 4.13%. The goal of the increase is to create overall congestion. Traffic from this region now needs to choose how to go around the city to reach the E314 highway and creates congestion on the Martelarenlaan (N292) and Tiensesteenweg (N3).

For the Flanders scenario, the counts for the OD that describe traffic between Ghent and Hasselt is increased. The overall increase in traffic is 5.04%. The goal of the increase is to create congestion on routes involving either the E40 or the E313 and E17 highways.

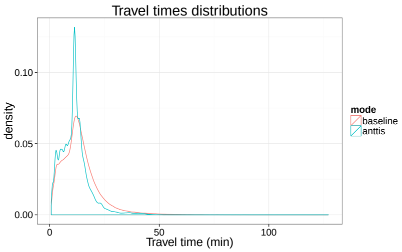
Analysis of the baseline

The travel time and distance distributions for the flow disturbed experiments (Figure 6.26) resemble those obtained in the network disturbed experiments. For the travel time densities in Figure 6.26a and 6.26c the difference between the travel times for the baseline and the guided vehicles is visible. The travel times in the baseline seem on average higher than those in the AntTIS guided case. For the distance distribution the center of the distances in the baseline and the AntTIS case seem identical. The shape of the distribution has changed.

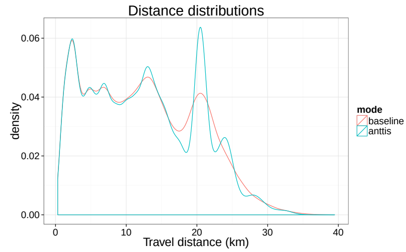
The q_d^b and q_l^b score distributions (Figure 6.27) confirm these observations. The average q_d^b has not shifted as far as in the experiments with the network disturbances. Figure 6.28 shows a comparison between the average q_d^b in the undisturbed and flow disturbed experiments. The means cluster around 0.864 with a standard deviation of 0.169 for Leuven and around 0.810 with a standard deviation of 0.194 for Flanders (Table 6.27).

Analysis of the participation rates

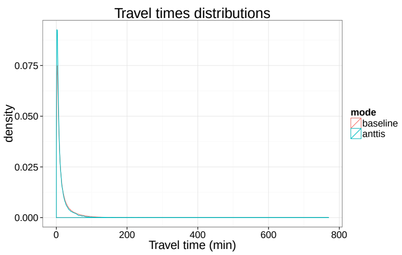
The observations for the undisturbed and network disturbed scenario can also be made for the flow disturbed scenario. For the simulation runs with 20%



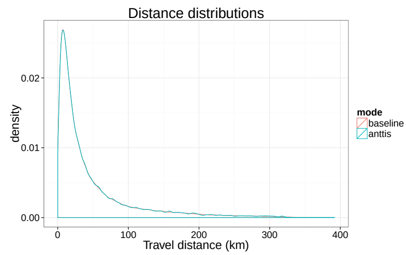
(a) Travel time distribution in Leuven



(b) Distance distribution in Leuven



(c) Travel time distribution in Flanders



(d) Distance distribution in Flanders

Figure 6.26: Distribution of the travel time and the distance for all routes in both the flow disturbed Leuven and the Highway scenario with flow disturbances.

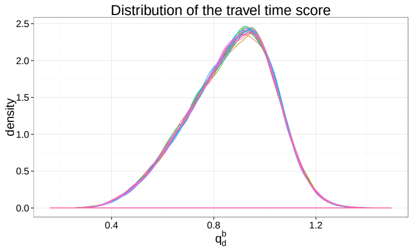
	mean	**std dev**	**N**
q_d^b	0.864	0.169	30
q_l^b	1.005	0.080	30

(a) Results for Leuven

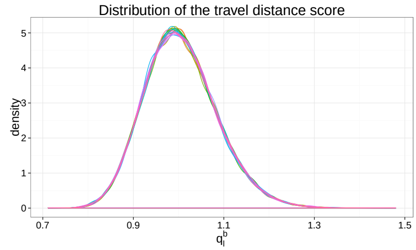
	mean	**std dev**	**N**
q_d^b	0.810	0.194	30
q_l^b	1.006	0.088	30

(b) Results for Flanders

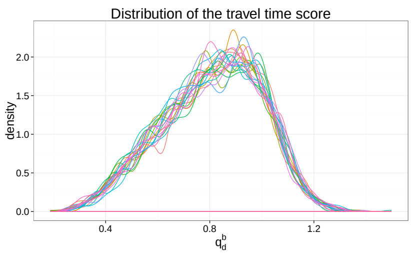
Table 6.5: Characteristics of the q_d^b and q_l^b metrics for the flow disturbed Leuven and Highway scenarios



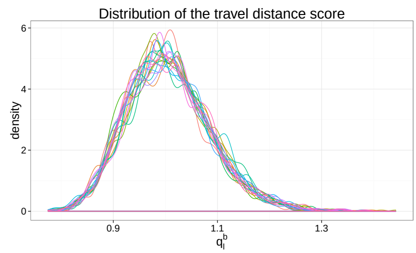
(a) q_d^b distributions for Leuven



(b) q_l^b distributions for Leuven



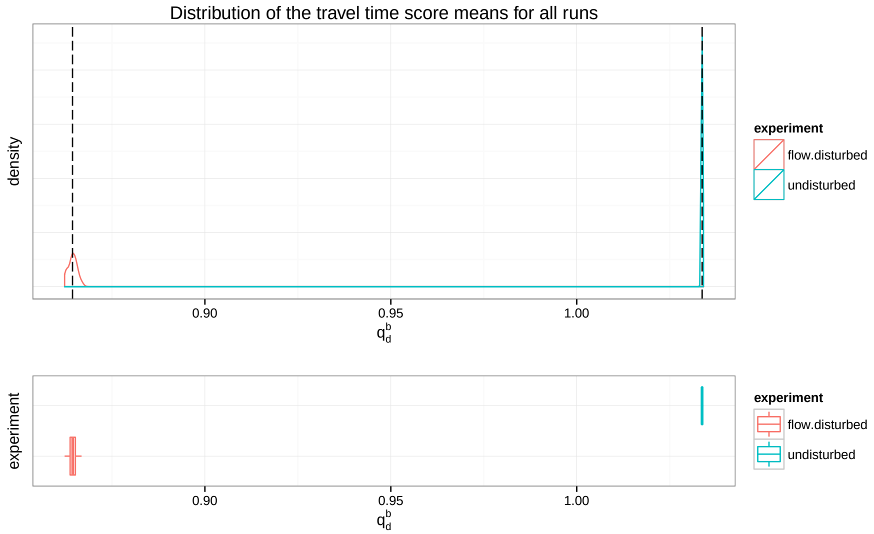
(c) q_d^b distributions for Flanders



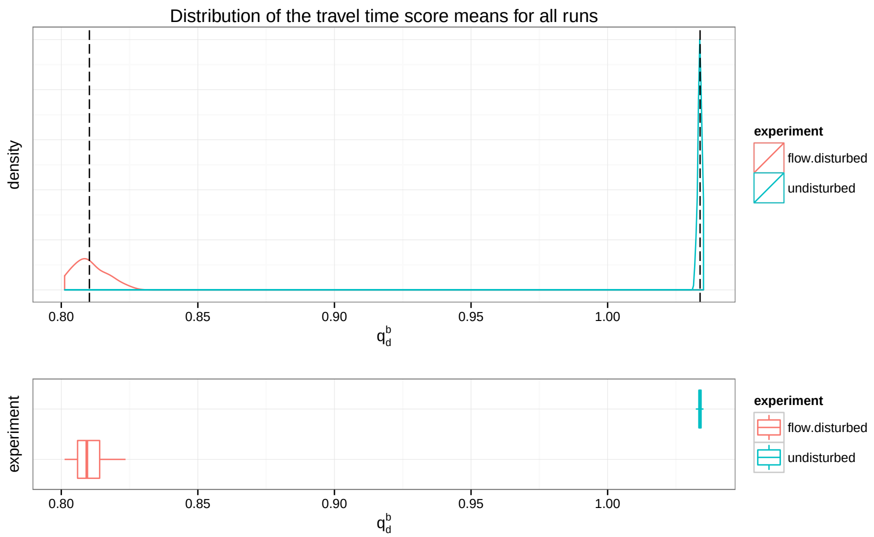
(d) q_l^b distributions for Flanders

Figure 6.27: Distributions of the q_d^b and q_l^b scores for the results obtained in both the flow disturbed Leuven and the Highway scenario. Every distribution corresponds to one de-aggregated version. A summary of the characteristics of the distribution can be found in Table 6.5

and 40% participation rate AntTIS offers no improvement over the baseline as shown in Figure 6.29 and Table 6.6.

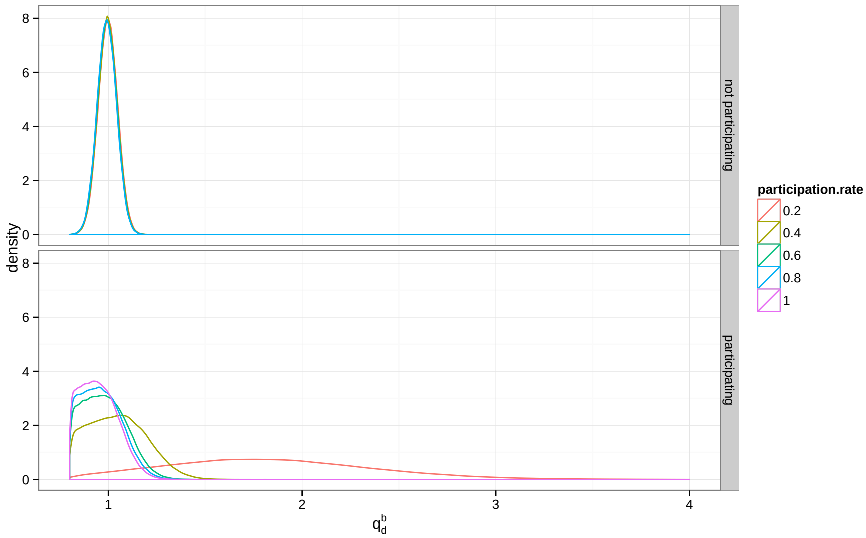


(a) q_d^b distribution for Leuven

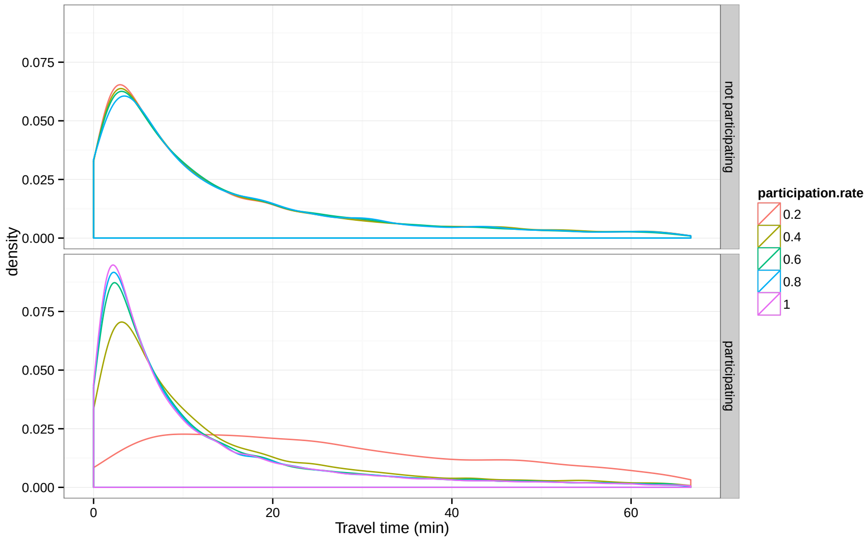


(b) q_d^b distribution for Flanders

Figure 6.28: Overall distribution of q_d^b values. The grey dashed line in the density plot indicates the average. These results are from the Leuven and Highway scenarios with flow disturbances.



(a) Travel time distribution for Leuven



(b) Travel time distribution for Flanders

Figure 6.29: Distribution of the travel times for both participating and non-participating vehicles in the experiments with varying participation rates. These results are from the Leuven and Highway scenarios with flow disturbances.

part. rate	$\mu_{\mathbf{np}}$	$\sigma_{\mathbf{np}}$	$\mathbf{N_{np}}$	$\mu_{\mathbf{p}}$	$\sigma_{\mathbf{p}}$	$\mathbf{N_{p}}$
100%	–	–	0	0.864	0.169	33838200
80%	0.991	0.050	6767640	0.881	0.172	27070560
60%	0.994	0.050	13535280	0.904	0.177	20302920
40%	0.996	0.051	20302920	0.999	0.200	13535280
20%	0.997	0.050	27070560	1.947	0.518	6767640

(a) q_d^b results for Leuven

part. rate	$\mu_{\mathbf{np}}$	$\sigma_{\mathbf{np}}$	$\mathbf{N_{np}}$	$\mu_{\mathbf{p}}$	$\sigma_{\mathbf{p}}$	$\mathbf{N_{p}}$
100%	–	–	0	0.810	0.194	440390700
80%	0.996	0.098	88078140	0.829	0.199	352312560
60%	0.995	0.098	176156280	0.871	0.209	264234420
40%	0.993	0.099	264234420	1.131	0.270	176156280
20%	0.990	0.100	352312560	5.851	1.456	88078140

(b) q_d^b results for Highway

Table 6.6: Characteristics of the q_d^b metric for the flow disturbed Leuven and Highway scenarios under various participation rates. The population mean μ, standard deviation σ and size N for both the participating p and non-participating np populations.

6.3.3 Conclusion for disturbed experiments

The analyses in this section leads to the following conclusions for the experiment with disturbances:

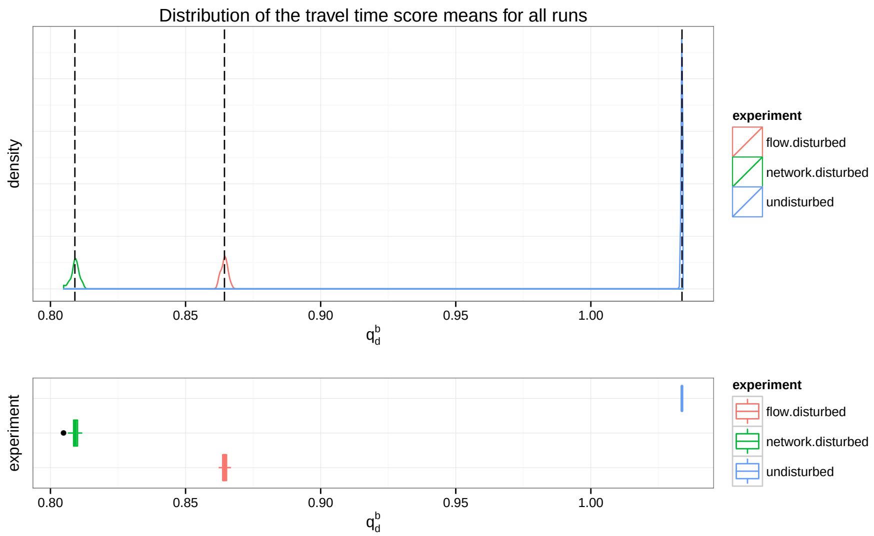
- In case of a disturbance, the routes offered by AntTIS lead to shorter travel times compared to the baseline scenario.
- The AntTIS provided routes do not differ much in terms of travel distance.
- The impact of the participation rates remains similar to the undisturbed experiments. For 40% and 20% participation rate, the benefits of AntTIS are lost and the route quality is worse than in the baseline.

In case of disturbances, be it in the traffic supply or in the traffic demand, the route guidance offered by AntTIS has a clear effect on the quality of the routes. Contrary to the undisturbed scenarios where the AntTIS routes where slightly worse than the baseline routes the scenarios with disturbances show a clear advantage for the AntTIS routes in terms of experienced travel time.

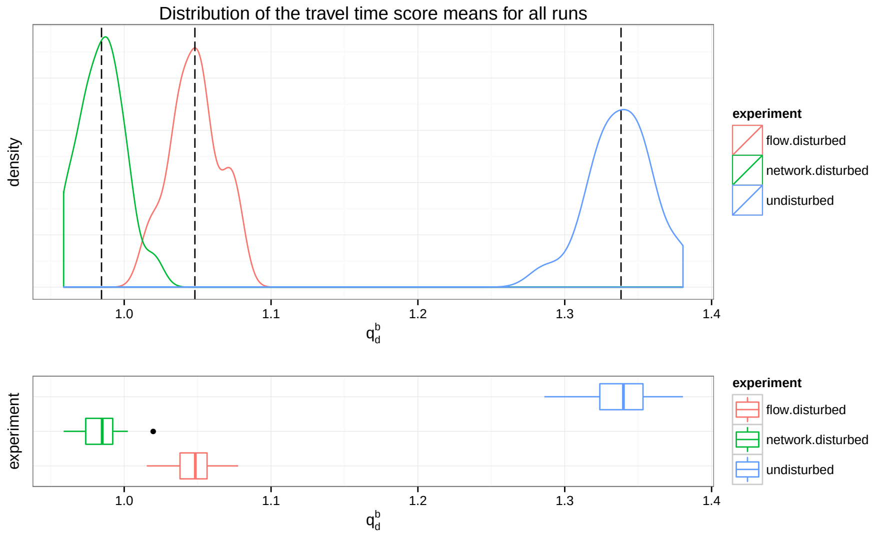
For the travelled distance, the results are less clear. While the distribution of the distances has changed shape. The q_l^b scores all cluster around 1. This trend was also observed in the undisturbed scenario and can be explained by the focus of the route guidance: minimize travel time.

Figure 6.30 shows the distribution of the average q_d^b for all runs. It is clear that the benefit of the AntTIS routes is bigger in the network disturbed scenario. This is not necessarily a characteristic of AntTIS. Figure 6.31 shows that travel times in the network disturbed scenario are much larger than in the flow disturbed scenario.

When dealing with network disturbances the resulting traffic network and its capacity will be unknown to the Infrastructure Agents responsible for the predictions. While the Infrastructure Agents learn about the changes in the network, the advise they provide to the vehicles will be no better than the advise given by route guidance based on real-time information such as Waze or Google Maps. Anticipating events that are unrelated to normal traffic conditions, such as accidents, is not something the ANNs are capable of.

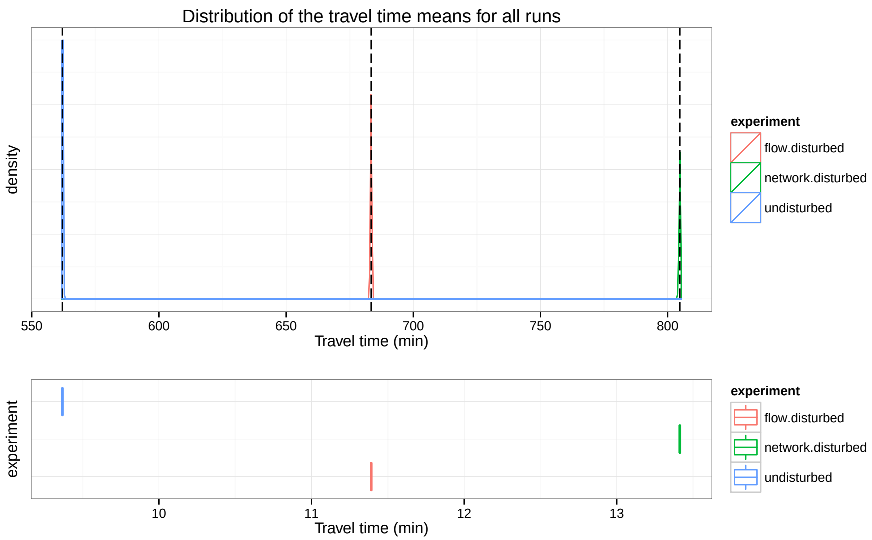


(a) q_d^b means distribution for Leuven

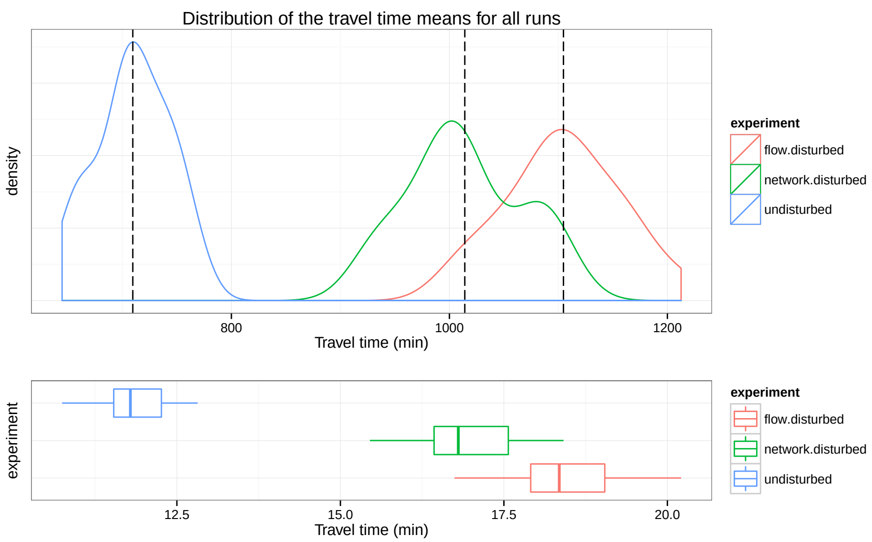


(b) q_d^b means distribution for Highway

Figure 6.30: The distribution of the q_d^b score for all experiments. The undisturbed, the network and the flow disturbed scenarios in both the Leuven and the Highway scenario



(a) Travel time means distribution for Leuven



(b) Travel time means distribution for Leuven

Figure 6.31: The distribution of the mean travel time for all experiments. The undisturbed, the network and the flow disturbed scenarios in both the Leuven and the Highway scenario

6.4 Conclusion

In this section we will discuss the hypotheses put forward in Section 5.1 and evaluate them based on the experiment results described thus far in this chapter.

6.4.1 Intention Propagation is able to predict traffic conditions

Hypothesis 1. Given sufficient participants sharing their intentions, the anticipatory vehicle routing system can accurately predict the traffic conditions during the time interval of the participants' trips.

As seen in Section 6.2.4 the ANNs in the AntTIS system are capable of predicting the link traversal times in the traffic network. The quality of the predictions decreases as the time horizon increases and the participation rate plays an important factor in the quality of the predictions.

6.4.2 Anticipatory vehicle routing leads to a user optimal route assignment

Hypothesis 2. The quality of the routes advised by the anticipatory route guidance system matches the quality of the routes in a user optimal route assignment.

The results described in Section 6.2.2 show that the values for the q_d^p metric are clustered closely around 1. This means that the travel times of trips in clusters of similar trips are similar. In other words, no driver has chosen a different route based on the information that was present amongst the drivers of that cluster.

This leads to the conclusion that the route assignment based on AntTIS is (at least an approximation of) a user optimal equilibrium.

6.4.3 Anticipatory vehicle routing benefits perturbated traffic networks

Hypothesis 3. Given a traffic network in which demand or supply is altered, the route quality of routes advised by the anticipatory route guidance system is better than that of drivers depending on their knowledge of the original traffic networks response to the original travel demand.

In both the experiment sets with perturbated traffic conditions (Section 6.3), the routes offered by the AntTIS system outperform those offered in the baseline case.

Travel times in the AntTIS guided experiments increased when the network was disturbed, something to be expected because of the decrease in network capacity or the increase in traffic demand. The increase, however, was less than that in the baseline scenario.

6.4.4 Anticipatory vehicle routing does not require complete participation

Hypothesis 4. The three previous hypotheses hold even when not all traffic participates. Not every driver has to share his intention with the system and follow the systems advice. There is however a critical threshold that must be met in order for the system to function properly.

For all experiments the influence of the participation rate was evaluated. As the participation rate decreases, the performance of the AntTIS system decreases. The link traversal time predictions become less accurate.

It is not until the participation rate reaches 40% that the effects become disastrous. At that threshold, the results obtained through AntTIS become unusable. Travel times for routes advised by AntTIS are a factor 2 to 3 higher if only 20% of the drivers participates.

A 40% participation rate is high. One 2 out of 5 drivers need to participate in the system, a penetration rate that is unrealistically high. To remedy the problems observed at lower participation rates, the AntTIS system will have to receive input from other traffic estimation systems.

Chapter 7

Related Work

The main characteristics of the AntTIS system described in Chapters 3 and 4 are its distributed nature, its anticipatory nature and the use of swarms of smart messages in the interaction between the main entities of the system, the Infrastructure and Vehicle Agents.

This chapter discusses these characteristics with respect to other related work. Specifically related work describing advanced traveller information systems (ATISs) that share one or more characteristics with the AntTIS system.

The chapter focusses on other ATISs that are either decentralized, anticipatory or both. The decentralized and anticipatory characteristics are the two most distinguished characteristics of the AntTIS system described in this thesis, so these two types of ATISs are most relevant.

Road users can be informed in a number of ways. AntTIS provides its users with information on which route they should follow. It provides route guidance to the road users. Other ATISs only inform their users of incidents or travel times through means of variable message signs or other road side signals. Such ATIS systems are excluded from the discussion.

Overview First Section 7.1 discusses a number of anticipatory ATISs that are also decentralized. Next Section 7.2 discusses systems that are anticipatory, but rely on one or more centralized components. Then Section 7.3 discusses ATISs that work in a decentralized manner. Finally in Section 7.4 we conclude the discussion on related work.

7.1 Decentralized Anticipatory Advanced Traveler Information Systems

This section describes a number of ATISs that are like AntTIS both anticipatory and decentralized.

Many of the ATISs discussed in this section and later on in the section on non anticipatory decentralized systems (Section 7.3) use information exchange patterns inspired by nature: the foraging behavior of ants or the evaporation properties of pheromones.

The delegate multiagent systems (dMASs) pattern used by AntTIS is also inspired by the behavior of ants. In many related literature, including the literature on Traffic Radar [69], the agents in the dMAS are called ants.

7.1.1 Ad Hoc Distributed Simulations

Ad Hoc Distributed Simulations [38, 52, 80, 108] is a traffic forecasting approach that uses distributed simulations to predict future traffic states. All vehicles participating in the system simulate the road network that is relevant to their routing choice. The outcome of the simulation is shared with road side infrastructure, but also with all other vehicles. The other vehicles can use the simulation outcome to update and refine their own simulations.

The in-vehicle simulations use real-time traffic sensor data, historic data and the data obtained from other in-vehicle simulations. All information is shared with road side infrastructure. There, a local server also simulates parts of the network and coordinates the simulation efforts for all vehicles.

The end result is a distributed parallel simulation of the entire road network. Every vehicle has the simulation results it is interested in thanks to the in-vehicle simulation. Contrary to other distributed simulations, parts of the traffic network in this simulation will be simulated in parallel in multiple simulations. This is not a drawback, but a feature that improves the robustness of the system. The fragment of the network simulated in one in-vehicle simulation can change over time as the vehicle changes progresses on its route and possibly makes new routing decisions. The system is also an open system. Vehicles will join and leave, causing existing simulations to suddenly disappear and new simulations to start.

The Ad Hoc Distributed Simulation approach is almost orthogonal to the AntTIS approach described in this thesis. Ad Hoc Distributed Simulations take the vehicles route as the basis for the travel time estimation. Information is aggregated based on the route of the vehicle, while in AntTIS information is aggregated based on the link it concerns. The in-vehicle simulations predict the travel time for one vehicle and share the resulting information with the other vehicles. In AntTIS the link traversal time for a link is predicted and vehicles can aggregate link traversal times for several links to predict their own overall travel time.

7.1.2 Anticipatory Stigmergy

Anticipatory Stigmergy [54, 81] uses stigmergy to predict future traffic conditions. Vehicles use stigmergy to store information about their travel times in a virtual environment. Both long-term and short-term trends are computed and stored. Vehicles can also use stigmergy to indicate where they are likely to be in 5 minutes time. This information is called anticipatory stigmergy.

In [54], a combination of long-term and short-term stigmergy is shown to outperform anticipatory stigmergy in a static network. The experiments are repeated in [81], and here anticipatory stigmergy outperforms the other stigmergy types in a network that is no longer considered static.

Similarly to Anticipatory Stigmergy, the Pheromone Model[7, 8] is a cooperative ATIS that uses the concept of digital pheromones [13] to inform users of real-time traffic information.

As vehicles move through the traffic network, they deposit digital pheromones in a pheromone potential field. The presence of a virtual environment capable of maintaining this pheromone potential field is assumed. The intensity of the pheromone deposits depend on the speed of the vehicle. Fast moving vehicles will deposit less pheromones than slow moving vehicles.

The pheromones are subject to evaporation and propagation. The pheromones are propagated upstream to predict future traffic conditions. Vehicles can then sense these pheromones and use the information represented by the pheromone levels to make routing decisions.

The Pheromone Model focus solely on stigmergy and pheromones to handle information. The pheromones do not contain information about expected travel times, they only give an indication to the road users how busy it will be in the future. The Anticipatory Stigmergy approach stores historical link traversal times in the stigmergic information. It also uses a heuristic based both on anticipatory stigmergy and historical traffic information to guide users.

7.1.3 Traffic Radar

Traffic Radar [69] is a holonic traffic coordination system that also uses the delegate multiagent pattern to provide anticipatory route guidance to users. The development of Traffic Radar as part of the MODUM project[1] originates from the same research into dMAS based coordination as AntTIS originated from [48]. Within the MODUM project Traffic Radar is used to provide multi-modal routing information to end users [64].

As such many of the characteristics in Traffic Radar are also present in AntTIS: swarm based interactions (Section 3.2) and refresh-and-evaporate (Section 4.2.2). Furthermore, the holonic architecture is very similar to the multiagent architecture described in this thesis. Instead of Vehicle Agents, Traffic Radar features Vehicle Holons and Infrastructure Agents have two counterparts that are called Node and Link Holons.

Their responsibilities are very similar. Vehicle Holons initiate the exploration and intention propagating dMASs. They are also responsible for calculating the routes. Link and Node Holons maintain the information on the vehicle intentions and maintain accurate traffic models describing the entity in the traffic network they represent.

Contrary to AntTIS, Traffic Radar does not consider traffic to be a black box that needs to be learned using machine learning techniques such as artificial neural networks (Section 4.3). Instead Traffic Radar uses the link transmission model [113] to predict traffic flows.

The link transmission model keeps track of cumulative vehicle flow at both the start and end of a traffic link. Such a cumulative vehicle flow describes the total number of vehicles passed at that point in the graph over time.

Traffic Radar uses dMASs to align the input to all link transmission model vehicle flows with the intentions of the vehicles and to synchronize the vehicle flows of the different links.

Traffic buildup, congestion and spill-over are modelled explicitly in Traffic Radar. The model used to calculate the link traversal times is much more powerful than the artificial neural networks used by AntTIS. The artificial neural networks on the other hand are a much more pragmatic solution with the following benefits:

- AntTIS can deal with partial participation. The participation ratio is taken care of by the artificial neural networks and their continuous training process.

[1] http://modum-project.eu

- AntTIS requires no modelling of individual roads. The specifics of roads are learned by the artificial neural networks as time progresses

7.1.4 Ant Based Control

This section describes Ant Based Control [59, 84, 82, 83] a route guidance system that has evolved over time from being a centralized routing system based on real-time traffic information to a decentralized routing system based on link traversal time predictions.

Dynamic traffic routing using Ant Based Control [59, 82] is an adaptation of AntNet, an Ant Colony Optimization based routing algorithm for telecommunication networks [28]. The main focus of the system is to include real-time traffic information in the in-vehicle route calculation process. Something that is difficult because often real-time information is only available for larger roads and highways.

Dynamic traffic routing using Ant Based Control, as described in [59, 82] is a centralized system. Vehicles all communicate with a *Routing System* and receive their precomputed routes from this system.

The Ant Based Control algorithm uses floating car data. It relies on the vehicles to determine their own position and their link traversal times. The data captured by the vehicles is handled by the *timetable updating system*. That system makes the information available to the *route finding system*.

The route finding system uses the real-time dynamic information gathered by the individual vehicles and uses the variant of AntNet to find routes for vehicles when they request a route.

H-ABC and Hierarchical routing system [83] are an extension of the centralized routing system. The system design is adapted and made decentralized. This solves earlier scalability issues and makes the approach more robust. Both information management and route finding now takes place in a hierarchical graph structure.

The hierarchical routing system divides the traffic network graph in a hierarchical way. The graph is divided into sectors, subgraphs of closely related links and nodes (a city for example). These sectors are represented as virtual nodes in a more abstract graph that describes the connections between the different sectors.

In the hierarchical routing system, nodes maintain tables of turning probabilities for all destinations in that sector. The probabilities represent the chance of a vehicle trying to reach a destination taking a particular turn. These probability tables are kept up to date and are queried using swarms of mobile agents called ants. The H-ABC system has three types of ants: local ants, backward ants and exploring ants. The functioning of the ants resembles the smart messages in AntTIS and the ants in Traffic Radar.

The exploration of the network is based on the movement of the exploration ants. Their movement is determined by the values in the probability tables stored in all nodes.

Travel Time Prediction for Dynamic Routing using Ant Based Control [84] further extends the H-ABC system to include travel time predictions and makes the system anticipatory. The predictions in the system are based on expected car counts, similar to the intention levels in AntTIS, and the relationship between traffic density and travel speed.

The probability tables maintained by the nodes are now made time dependent. Next to the probability tables, the nodes also keep track of the number of vehicles expected on each link and the expected travel times for all time intervals.

Information on the expected vehicle counts is maintained in a similar way to AntTIS. If no update is received after a certain period of time or if the vehicle visit is in the past, then the information is discarded.

Whereas in AntTIS routing is done explicitly by the Vehicle Agents and the smart messages are only used to evaluate the proposed routes, Ant Based Control takes an approach closer to Ant Colony Optimization and AntNet and delegates this responsibility to the ants. This requires more information to be maintained by the agents representing the environment. In this case the agents responsible for the nodes. They have to maintain the probability tables that allow the exploration ants to find good routes.

In AntTIS route candidates are calculated based on static traffic information instead of on real-time or predicted information. The routes are later on evaluated based on predicted traffic information. If the discrepancies between static and predicted traffic data grows very large, it is possible for AntTIS to exclude certain routes.

In [20, 23] we experimented with a route finding algorithm that follows the philosophy of ant colony optimization and AntNet. This algorithm resembles the algorithms used in Ant Based Control. The benefit of delegating the route calculation to the swarm was not sufficient in realistic networks.

Contrary to AntTIS and Traffic Radar, Ant Based Control has a very simple prediction model, the relationship between traffic speed and traffic density. This is then combined with historical traffic information. Phenomena not local to a link such as spill-over are not captured by this model.

7.2 Anticipatory Advanced Traveler Information Systems

This section describes some other anticipatory ATISs. The systems described here are selected based on their relevance and resemblance to the AntTIS system described in this thesis.

The ATIS systems described in this section are not necessarily distributed or decentralized. ATIS systems with a decentralized or distributed structure, but operating based on real-time or historical traffic information are discussed in Section 7.3.

7.2.1 SAVaNT

The SAVaNT (Simulation of Anticipatory Vehicle Network Traffic) system [109, 57] is an ATIS that provides its users with predictive link traversal times. In that sense, the SAVaNT system is similar to the AntTIS system described in this paper. While the end goal of both systems are similar, the manner in which this goal is achieved differs greatly between both systems. The main differences lie in how the system is structured.

In [109], Wunderlich et al. define an anticipatory route guidance as a system in which:

> Anticipatory route guidance can be defined as paths calculated from a set of predicted future link travel times, which, when disseminated to drivers, cause the same set of predicted link travel times to be realized by vehicles in the network.

The route choice based on these paths leads to a user optimal equilibrium.

The link traversal predictions in SAVaNT are based on traffic simulations using the INTEGRATION traffic simulator [88]. This simulator is used in an iterative manner to achieve a fixed point assignment. A dynamic router R calculates a complete routing policy π_i based on a link travel time profile C_i. This policy is simulated and results in a new link travel time profile C_{i+1}. A routing policy π is considered a fixed point assignment if subsequent iterations result in the same outcome.

These link travel time profiles are disseminated to the users of the ATIS system. The users of the system can use these link travel time profiles to calculate their optimal route. This leads to *All-or-nothing routing*. If all users optimize their own route, users with similar origin and destination pairs will all choose the same route.

The SAVaNT system is described by the authors of [109] as a decentralized routing system. However, their definition of a decentralized system differs from the one used in this thesis. In this thesis we look at the overall architecture of the ATIS system to decide whether or not it is decentralized. In the papers discussing the SAVaNT system, the distinction is made on the route choice level. If the route choices are made in the vehicle, then the system is decentralized. If the route choices are made by one central *Information Service Provider* (ISP), then the system is considered centralized. By this definition, the SAVaNT system is considered decentralized because the route selection is done in the vehicles based on information sent to the vehicles by an Information Service Provider.

7.2.2 Route Information Sharing System

The Route Information Sharing System (RIS) [110, 111, 112] is an ATIS that operates on the same premises as the AntTIS system. Namely that onboard car navigation systems have access to the currently chosen route for their drivers. If that information is gathered and aggregated, it leads to information about future traffic states. Information that can be used to adjust road users route choice.

In RIS, all drivers share their routes with one central system: the route information server. The route information server collects all route information from all RIS drivers and aggregates it per link. The aggregation in RIS is done using a *passage weight*. This passage weight is used to take into account the uncertainty of a vehicle actually passing on the link. The passage weight is calculated as follows: The links in a vehicles route are assigned an index in ascending order from the destination of the vehicle up to its current position. So if there are p links in the vehicles path, then the link leading to its destination is assigned $1/p$ while the vehicles current link is assigned p/p.

Thus the value of the passage weight indicates a certainty that the vehicle will pass on the link it currently occupies (a passage weight value of 1), while links further along the route will get ever decreasing weights.

The route information server calculates the total passage weight for a link by summing up all the passage weights for that link. This total passage weight is combined with the expected travel time to calculate the prospective traffic volume. The prospective traffic volume of a link l is defined as:

$$PTV_l = ETT_l \times (TPW_l + \alpha) \tag{7.1}$$

Where α is a positive constant. In the evaluation of RIS, α is set to 1.0. This prospective traffic volume is then sent back to all drivers participating in the RIS system. The drivers use this information to update their intentions. Afterwards the process repeats.

The design of RIS shares some concepts with that of AntTIS. Both rely on the road users to share their routes with the system in return for information about future traffic states. Furthermore, RIS also assumes there is a relationship between the passage weights for a link, a concept that resembles the intention levels for a link in AntTIS, with the link traversal time a road user is likely to encounter on that link in the future.

The evaluation of RIS system shows some trends also observed in the evaluation of the AntTIS system. First the observation that participating drivers benefit from participating and have shorter travel times. Secondly, the observation that as the number of participating drivers increase, the benefit for the participating drivers increases.

The last observation somewhat contradicts the observation made for AntTIS, namely that when the participation rate increases, the benefits for the participating drivers decreases and the benefits for the non-participating drivers increases. An observation that was also found for other ATISs [57]. This contradiction is probably due to differences in the experiment setup. The decrease in benefit for the participating users is most likely due to increase in use of alternative routes as more and more participating users try to avoid congestion buildup. If the capacity on the alternative routes is sufficiently hight, then there is no penalty for the increase in its usage because of the increase in participation. The participating drivers then only benefit from the increase in participation because the predictions become more accurate.

While RIS shares some basic principles with AntTIS, it differs in some key aspects:

- RIS is described as a centralized ATIS solution. The route information server receives information from all drivers and maintains the total passage weights for all links in the system. In their paper [111], Yamashita et al. acknowledge this problem:

> However, if we were to apply such an RIS system on a huge road network like the one in Tokyo metropolitan area, direct communication by phone would be impossible because the route information server could not deal with the heavy communication traffic.

To remedy this problem they propose an intermediary level that collects the route information sent by drivers and sends it in batches over high speed dedicated lines. The role of these information proxies could be played by the traffic light infrastructure.

- The RIS system does not assume total participation of all road users. The evaluation of the RIS system shows how it compares depending on the participation rate of RIS users. How the participation rate is taken into account is unclear. The information that is shared with the users of the system is likely only used to compare between different route alternatives and not to indicate an ETA. If the participation rate is assumed to be equal throughout the system, then the ratio is eliminated when comparing two prospective traffic volumes.
- The information shared with the road users in the RIS system is different from that shared with the road users in the AntTIS system. In the RIS system the road users receive the prospective traffic volumes (PTVs). These prospective traffic volumes are used instead of link traversal times to calculate the best route. The PTV values are time independent and do not give an indication on when the road user will reach his destination.
- The information maintained by the route information server appears to be time independent in RIS. Whereas in AntTIS the intention levels are defined as a function over (a discretized) time. How this affects the efficiency of RIS in very dynamic traffic situations is unclear.

A more detailed comparison between RIS and AntTIS is difficult because the description of RIS lacks some details. It is not specified how the route information server shares the prospective traffic volumes with the road users.

7.3 Decentralized Advanced Traffic Information Systems

The ATISs described in this operate on real-time or historical information. The reason they are included in this discussion is that the way they disseminate information is comparable or relevant to how information is disseminated in the AntTIS system.

7.3.1 BeeJamA

BeeJamA [74, 99] is distributed routing protocol that guides individual road users with the intention of avoiding congestion. Like Ant Based Control, it takes inspiration from social insects. Here the approach draws inspiration from the behavior of honey bees. Also like Ant Based Control, BeeJamA is an adaptation of a communication network routing protocol: BeeHive [98].

The focus in BeeJamA is information dissemination. BeeJamA works under the assumption that because the system reacts very fast to changes in the traffic network, it makes forecasting these changes unnecessary.

BeeJamA employs a V2I infrastructure not so different from the one proposed in Section 3.1. Navigators are agents running in the traffic network infrastructure. These navigators communicate with personal navigation assistants (PNAs) running onboard of the vehicles. These PNAs inform the navigators of the traffic conditions they encounter. The information shared by the PNAs can be augmented with floating car data from other sources.

All navigators emit mobile agents, called bee agents. These bee agents flood the network. As the bees propagate through the network, they inform the navigators they encounter on the travel time from their current node to the node where they originated. Navigators can use this information to guide the vehicles in their section of the network.

Similarly to the foraging behavior of honey bees, the bee agents will travel various distances. Some bee agents will only travel in the vicinity of their origin. Other bee agents will travel in an overlay network and inform navigators that are further away. This enables the BeeJamA algorithm to scale to larger networks.

The structure and design of BeeJamA resembles that of AntTIS. The traffic network is divided into smaller sections and Infrastructure Agents or navigators manage the information for that section. There are also important differences between BeeJamA and AntTIS:

- BeeJamA does not provide road users with complete routes. Instead of informing road users about their entire trajectory, BeeJamA only informs road users of the next route decision they have to make.
- BeeJamA does not anticipate future traffic states and congestion. This is a clear design choice. BeeJamA is a reactive approach and will only start guiding vehicles away when congestion starts to form.
- BeeJamA works in a hierarchical network structure. This structure is needed to keep the network flooding by the bee agents manageable at a larger scale. AntTIS only propagates smart messages over the relevant agents and uses this technique to manage the audience size of a message.

BeeJamA is very similar to earlier versions of Ant Based Control, specifically the hierarchical version H-ABC discussed in Section 7.1.4.

The original BeeJamA algorithm does not take into account the reservation of links. A path reservation extension was developed [73] and improves the results of the original protocol when the participation rate is at least 40%.

7.3.2 SOTIS

SOTIS (Self Organizing Traffic Information System) [106, 105] is an ATIS that is able to operate without any road side infrastructure. The system is self-organizing and relies on the cooperation of all participating vehicles to capture and disseminate real-time traffic information. SOTIS was developed as art of the FleetNet Project[2]

The designers of SOTIS argue against centralized ATISs relying on TMC broadcasts and road sensors. Instead the designed SOTIS as a self-organizing system. The state of traffic is measured by the vehicles participating in the system using their on-board GPS unit. This information is shared with all surrounding vehicles. Eventually the SOTIS technique ensures that each vehicle knows about the traffic situation in the surroundings for a radius of approximatly 50 to 100 km.

The SOTIS system is capable of assessing and disseminating traffic information even if only 2% of the vehicles participates in the system. Traffic information is

[2] http://www.fleetnet.de

sent to nearby vehicles. Those vehicles interpret and analyze the data, combining it with the knowledge they already had, before forwarding the information they themselves belief to be true.

Thus every individual vehicle takes on the role previously taken by the central traffic information service. The rational behind this is that it is information about the close proximity of a driver that is most likely to influence his decisions.

7.4 Conclusion

This section introduced many ATISs capable of routing road users towards their destination. Many of these systems are, like AntTIS, decentralized and many are anticipatory.

Systems that are both anticipatory and decentralized often take inspiration from systems occurring in nature to help them deal with scalability and to structure the information dissemination.

Many of the anticipatory systems base the traffic forecasting on information aggregated in a virtual environment. AntTIS does this using intention levels, other approaches use concepts called passage weights or pheromones. The basic principle is the same: store information about pending vehicle visits in a virtual environment, aggregate that information and map it onto link traversal times.

Chapter 8

Conclusions

Our dependence on road traffic for our daily transportation needs does not seem to decrease. Many traffic networks are saturated by the huge demand. It is this problem that the work in this thesis addresses.

This thesis takes the coordination mechanism based on delegate multiagent systems (dMASs) and describes how it is adapted into AntTIS, a decentralized multiagent system (MAS) capable of anticipating future traffic conditions and guiding road users based on those predicted traffic states.

This addresses the two problems that where stated in the introduction:

- Short Term Traffic Predictions
- Coordination of a large scale and highly dynamic system

We have shown that using traffic can be predicted using the information contained in the intentions shared by the road users. The use of MASs and MASs enables a swarm based interaction between the geographically distributed entities in the system.

8.1 Contributions

This thesis describes three contributions that allow dMAS to be applied in a traffic context:

- **Delegate multiagent systems based evaluation of routes in large-scale traffic networks [16, 19, 20, 23]** Exploring large-scale graphs in search for suitable routes using only the ant colony optimization based approach described in the original dMAS based coordination and control applications was not possible in the traffic context. By exploiting the fact that the structure of the traffic network is not dynamic and existing graph searching algorithms the exploration and evaluation of only a selected set of suitable routes was possible.

- **Short term traffic predictions using machine learning in dynamic traffic networks [16, 19, 24]** The rigid reservation based system in the original dMAS based coordination and control systems was not suited for traffic due to the very dynamic nature of the domain and the uncertainty due to a lack of total control over the vehicles and outside influences. Instead of assessing estimated time of arrivals (ETAs) and estimated time of departures (ETDs) based on reservations, the AntTIS system uses machine learning to make predictions.

- **Intention level information aggregation [18, 16, 19, 22, 25, 24]** Storing the information provided by the vehicles in a way that it can be aggregated and used as input for the machine learning algorithm, and still can be maintained was a challenge. By storing the individual intentions and aggregating them into intention levels both requirements were met.

The evaluation of the AntTIS system also resulted in a simulation framework that can be and has been reused to evaluate other coordination mechanisms [17, 21, 26].

8.2 Future Work

This section describes opportunities for future work based on the contributions described in this thesis.

Using AntTIS to guide road users towards a system optimal equilibrium

AntTIS only provides road users with accurate and honest information. The road users that make decisions based on this information will make selfish decisions: they will try to minimize their own travel time. Because of this behavior, the use of AntTIS will lead to a user optimal equilibrium in the traffic network.

The traffic network could be used more efficiently if the system would guide the users to a system optimal equilibrium. Providing road users with inaccurate information to alter their decisions and steer them towards a system optimal choice would only undermine the cooperation between the AntTIS system and the road user. To alter the road users behavior an external incentive is required.

Integrating such an external incentive is still future work. Providing a road user with guidance that considers more parameters than just travel time, but also for example travel cost due to road pricing schemes, remains a challenge. The current AntTIS system only tries to minimize travel time. Minimizing travel times *and* travel cost would complicate how a Vehicle Agent chooses deals with the intention revision process.

The predictive capabilities of AntTIS represents an opportunity in dynamic road pricing. By aligning road prices with the expected future use of a road the system would be able to steer road users behavior dynamically towards a system optimal traffic assignment. The predictions could be used to better approximate the actual marginal cost associated with the use of a link in a trip. This would make the incentive caused by a toll more effective [75]

Modelling traffic spill back as inter-agent interactions

MASs work well in cases where information is local. At a first glimpse the information contained in road users intentions is local and only affects the traffic conditions on the traffic link it pertains to.

Traffic networks have two basic types of propagation. Cars propagate forwards through the network. Congestion however propagates backwards. Just as cars can drive from one link to the next, congestion can spill back from one link to a previous one.

Because of this, congestion can form on a link while the intentions describing the future use of that link do not indicate heavy use of that link. The cause of the congestion is contained in the information present in the intentions further downstream in the traffic network.

The AntTIS system only partially handles this complication. Some information is exchanged between the individual Infrastructure Agents. The interaction between the Infrastructure Agents does not take into account the underlying traffic dynamics. If congestion is detected, that information is relayed upstream. The information is however rather limited. The information that is exchanged could be made more complex, allowing the Infrastructure Agents to inform others better of congestion and spill back.

Infrastructure Agents could be made to explicitly handle spill over and could use information about the underlying traffic network to inform other Infrastructure Agents about upcoming congestion and the possibility of spill over. This addition could require a more transparent prediction model such as the one used in the Traffic Radar approach [69]. Traffic Radar already handles spillover explicitly.

Model road user behavior to assess its influence on intentions

The evaluation in this thesis assumes full cooperation from road users. This assumption is based on the fact that road users are given accurate and helpful information and it is therefor in their best interest to follow the instructions given to them.

Numerous studies show that in real world scenarios, road users do not always take the decision that is expected. This could influence the performance of advanced traveller information system (ATIS) systems such as AntTIS [3, 58, 4]. Evaluating AntTIS while taking into account the decision process of the road user remains future work.

Impact of privacy enhancing techniques on AntTIS

The right to privacy of the road users participating in the AntTIS system was left outside of the scope of this thesis. It should not be kept out of scope. ATIS systems gather vast amounts of data on the travel behavior of their users. AntTIS also does this. This is a privacy problem [5].

While privacy was kept outside of the scope of this paper, privacy in ITS and ATIS systems is a well researched topic[78, 6]. Techniques such as the use of pseudonyms, anonymisers and Private Information Retrieval (PIR) can be used to improve the privacy of the users of ATIS systems such as AntTIS.

How these techniques can be implemented in the AntTIS system and how they impact the performance of the system is future work.

Applicability of the approach

This thesis describes AntTIS and the results that can be obtained in a simulated environment. For the system to be deployed, more insights are needed into the communication and computational requirements. By measuring the impact of the communication overhead [22], we have already started this analysis. A more thorough and complete assessment remains future work.

The technological requirements of the system do not differ much from currently available state-of-practice route guidance systems. Route guidance systems such as Google Maps or Waze already require the deployment of computational devices on-board vehicles. These devices also require internet access. The AntTIS system could also operate over the internet.

On the prediction side, the requirements of AntTIS are more demanding. AntTIS requires real-time access to traffic information and a large number of measurement stations. The large number of measuring stations contributed to requirement for a decentralized architecture for AntTIS. The requirements of AntTIS are not met in todays traffic infrastructure.

8.3 Closing Reflection

This research on anticipatory vehicle routing started out as an exercise in adapting the dMASs based coordination mechanism to the domain of traffic guidance. Little of the original coordination mechanism remains in the version described in this thesis.

Route guidance and traffic state prediction are both very large research domains in their own right. The advances in those domains have swept in and replaced many of the building blocks previously used. The size, dynamism and open nature of traffic poses unique challenges for coordination mechanisms. In this thesis we have tried to meet those challenges by using patterns and tactics based on MASs and dMASs.

In some ways the AntTIS system described in this thesis has evolved into something very different than the original MASs described in Section 2.4. In that evolution and the decisions that drove it lie the main contributions of this thesis. Those decisions are influenced by research in traffic simulation, MASs, ITS and many other domains.

Science, my lad, is made up of mistakes, but they are mistakes which it is useful to make, because they lead little by little to the truth.

– Jules Verne, *A Journey to the Center of the Earth*

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